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Essays on Commercial Mortgage-Backed Security

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Dedicated to my parents and my wife Yun Zhou.

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Essays on Commercial Mortgage-Backed Security

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Structured finance products including Commercial Mortgage-Backed Security (CMBS) suffered tremendous losses during the 2008 financial crisis. My dissertation consists of three chapters that contribute to our understanding of the causes of the crisis.

My first chapter is an empirical study on potential misrepresentation of CMBS. Although CMBS suffered large scale losses during the past financial crisis, currently, this segment of the structured finance market has almost recovered to its pre-crisis level. While evidence was found regarding the systematic misrepresentation of loan quality information for residential mortgages, there was no evidence of large scale misreporting for CMBS. This paper examines important financial variables reported in financial documentation of commercial mortgages such as Underwritten Net Operating Income (UW NOI). I find that, prior to the financial crisis, UW NOI was consistently over-estimated by an average of 7.8%. This overstatement lead to Loan-to-Value ratio and Debt-Service Coverage Ratio being misreported as 67.1% from 84.2% and DSCR as 1.72 from 1.59. The levels of aggregate over-estimation substantially differed

among originators and the variations explained the performance differences between originators. Each 1% increase in over-estimation resulted in a 20% higher likelihood in delinquency. The ratings issued by rating agencies failed to capture the adverse impact from over-estimation on CMBS performance.

The second chapter of my dissertation studies the CMBS credit rating market using a strategic interaction model. The 2008 financial crisis that arose in the mortgage market has brought renewed attention to the failure of the credit rating mechanism. Using Bloomberg data, I conduct a structural analysis of strategic credit rating behaviors in the Commercial Mortgage-Backed Security (CMBS) market. This chapter models the CMBS credit ratings as strategic behaviors that reflect the peer effects from other rating agencies. Peer effects are incorporated through the estimation of market "beliefs" about the ratings. We establish semiparametric identification of the model by exploiting an exogenous equilibrium shift due to the financial crisis. Moreover, the model is estimated using a two–step estimation procedure. The empirical results strongly support the presence of positive peer effects. By including peer effects, the fitness of our model has been significantly improved.

The third chapter examines the entrant-related consequences in the CMBS credit rating market after the financial crisis. I find that the entrant has given more lenient ratings than the incumbents. Among securities that obtained ratings from both entrant and incumbent rating agencies, 13.8% are granted a higher rating from the entrant than the incumbents from 2011-2014. In addition, deal level and loan level analyses further provide evidence that the entrant granted CMBS with 2.25% higher AAA-rated portion while the underlying loans in these CMBS are 10% more likely to become delinquent than other rating agencies. The lenient ratings from the entrant coincide with the sharp increase in the entrant's market share.

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Chapter 1

Examination of Potential Misrepresentation in CMBS

1.1 Introduction

In the aftermath of the financial crisis, a growing amount of studies have been focusing on related parties's roles in the formation of the crisis. Related to the massive and unprecedented defaults and losses brought on by residential mortgages and the structured finance products whose main underlying assets are mortgages, increasing focus has been placed on mortgage-related fraud from regulators (FBI, SEC and FHA), the media, and the academic world. For example, **?** and **?** demonstrate large scale misrepresentation in residential mortgages-backed securitized (RMBS) before the crisis. Their studies argue that second-lien loan status, owner-occupying status, and property appraisal value were largely misreported prior to the crisis. More importantly, the identified misreporting is associated with significantly higher default probabilities, and consequently, has resulted in the loss for RMBS backed by these mortgages.

Despite the intense scrutiny and attention brought on by the losses and downgrades in Commercial Mortgage-Backed Securities (CMBS) during the crisis[1] and the misreporting in RMBS, no reports or studies have revealed systematic misreporting in commercial mortgage origination. Meanwhile, new CMBS issuance has nearly recovered to its pre-crisis level in terms of number of deals issued.[2] The CMBS market seems to be shrugging off the bad publicity and heading to another boom market.

In this chapter, I examine the potential misreporting in commercial mortgages securitized into CMBS using detailed loan level data from Bloomberg Professional. The main financial variable focused on in this dissertation is Underwritten Net Operating Income (UW NOI). I begin by comparing the UW NOI to realized NOI at the end of the origination year. UW NOI was inflated by, on average, 4.8% for the years between 1995 and 2006. As the crisis approached, CMBS grew rapidly; the over-estimation was more severe. During 2003-2007, despite the booming real estate market and good economic conditions, the average over-estimation reached 7.8%. The economic consequences for the difference between UW NOI and realized NOI were substantial. If all loans were re-appraised using unbiased estimation with the same capitalization rates, the average Loan-to-Value (LTV) ratio increased from 67.4% to 84.2% and the average Debt-Service Coverage ratio (DSCR) deteriorated from 1.67 to 1.48. The differences substantially increased the risk and pricing of the mortgage. Consequently, it resulted in a higher demand for subordination

[1]For 2005 to 2008 vintage, the average downgrades are 10 notches, equivalently, from AAA to BB+.

[2]Number of deal issuances for US non-agency CMBS peaked at 158 in 2006, dropped to 26 in 2009, then recovered to 124 in 2013. In comparison, RMBS and CDO (not including CLO) issuance after crisis is a small fraction of its peak level in 2006.

level for the corresponding CMBS by investors and rating agencies. Higher AAA subordination levels certainly reduced the downgrades and defaults that occurred during the crisis.

The realized NOI of the origination year is an ex-post measure for UW NOI. Thus, two alternative explanations could justify the over-estimation. First, the over-estimation may simply be caused by unexpectedly low realization of NOI. Second, the more interesting case – the over-estimation – is caused by biased estimation generated by originators and borrowers in order to make the loans appear less risky. This dissertation formally lays out five hypotheses to test for these two alternatives. The results reject the null hypothesis and imply that a significant part of the over-estimation is attributed to biased UW NOI at origination.

This study also documents the large cross-sectional differences in over-estimation and probability of delinquency group by originators; more importantly, these two fixed effects are highly correlated with each other. Among eighteen originators that have at least 500 loans with available data during the sample period, seven originators with significantly positive over-estimation fixed effects from regression analysis have, on average, 10.6% over-estimation from 2003-2007. Over-estimation is sensitive to the marginal benefit of inflating the UW NOI and over-estimation is higher at securitization thresholds for key risk characteristics. Originators are at least partially aware of the over-estimation since loans with over-estimation tend to have a higher interest rate. The variations in the originator level of over-estimation explain the performance differences among originators. According to the result of logistic regression, each 1% increase in UW NOI over-estimation results in a 20% higher likelihood in severe delinquency.

I then examine whether CMBS investors are fully compensated for the over-estimation in terms of higher AAA subordination level. While deal level over-estimation of NOI has an impact on deal performance with respect to delinquency rate, there is no evidence showing that the CMBS with more over-estimation has a higher AAA subordination level. The finding implies the rating agencies are unsuccessful in using their private information and rating models to evaluate the quality of the security.

The rest of this chapter is organized as follows. The next section provides a background on misreporting in RMBS and a comparison between CMBS and RMBS. Section 3 describes the Data. Section 4 focuses on the main variable of interest, UW NOI. Section 5 uses five hypotheses to test for the two plausible alternative reasons for over-estimation. Section 6 presents the results on the relationship between over-estimation and loan performance. Finally, Section 7 discusses results related to pricing and rating agencies followed by a conclusion Section 8.

1.2 Background

1.2.1 Misrepresentation in Residential Mortgage

After the realization of large scale losses in RMBS, whether misrepresentation on loan quality information contributed to the massive defaults of mortgages was a question to be answered by investors, regulators, and researchers. In 2011, the Supervisory Insights by FDIC said "approximately one-third of all mortgage fraud cases in 2010 involved appraisal/valuation fraud."[3] From 2008-2012, there were at least 58 legal cases regarding the material breach of representations and warranties of residential mortgage-backed securities (**?**). Investment banks have settled for dozens of billions of dollars for fraud related to RMBS misrepresentation.

? examine three types of misreporting in securitized residential mortgages. Their study merges the non-agency securitized loan database (ABSNet) with the county property transaction record database (DataQuick). By comparing the two databases, the authors identify 13.4% of loans marked as having no second lien, do appear to have a second lien. 7.7% of loans reported as being owner-occupied, do not appear to be owner occupied. Moreover, by comparing the appraisal value derived from reported LTV ratio to an industry-leading automated valuation model (AVM), their article concludes that 17.8% of homes have appraisal values inflation. The study also shows this misreporting is associated with a 51% higher probability of delinquency.

?, in a parallel study, also examine the misreporting in residential loans. Their study focuses on two of three misreporting presented in an article by **?**: second lien and owner occupancy misreporting. The authors utilize two different databases and obtain similar results in terms of scale of misrepresen-

[3]https://www.fdic.gov/regulations/examinations/supervisory/insights/siwin11/siwin11.pdf

tation and impact on default probability. The study finds that, although the misreporting was partially priced in via higher coupon for misreported loans, interestingly, the RMBS investors were not fully compensated by either higher yield of the security or higher subordination level for AAA-rated tranche.

1.2.2 CMBS Background

The annual issuance for non-agency CMBS grew rapidly from 57 billion in 2000 to 269 billion in 2007. During the financial crisis, CMBS suffered tremendous losses due to high delinquency. The market was almost completely shut down in 2009 and 2010 when the annual issuances were merely 24 and 22 billion dollars. After the meltdown from the crisis, the structured finance industry attempted to restart the market and CMBS issued since then are called "CMBS 2.0". The industry deems "CMBS 2.0" a euphemism for "lessons learned."[4] The annual issuance recovered to 90 billion in 2013 and the number of deals issued has almost recovered to its pre-crisis level.[5]

Some extant literature studies the CMBS market. Asymmetric information and adverse selection are two of the important features in the securitization market. During the securitization process, the information related to the risk of the property and borrower is compressed to summary indicators such as LTV and DSCR, which serve as rating models inputs and the variables describing the risk of the CMBS in its prospectus. The originators for

[4]CMBS 2.0: What is it? from Dechert LLP Feb 13, 2012.

[5]In contrast, the RMBS issuance for 2013 is only 10% of its 2006 level.

commercial mortgages are categorized into two types: a conduit lender, who originates loans for direct sale into CMBS, and a portfolio lender, who sells part of their mortgage portfolio to CMBS. **?** show that investors are compensated by 33 bps for commercial loans from portfolio lenders compared to conduit lenders. However, **?** find that loans originated by conduit lenders have a higher hazard rate for default. **?** attribute the expansion of the issuance and inflation of the ratings of the pre-crisis CMBS to excess demand created by the loosening capital requirements on investment grade CMBS in 2002. That year, the regulatory change by the SEC lowered the capital requirement for senior CMBS tranches compared to directly holding commercial loans. The authors also show that, although there were few changes in the quality of the assets, the persistent reduction in subordination level for senior bonds lead to losses for senior CMBS tranches during the financial crisis.

1.2.3 Comparison between Residential and Commercial Mortgage Origination Process, and Implication on Potential Mis-reporting

Compared to residential mortgages, the commercial mortgage appraisal process involves more soft information, which is property-specific, subjective information. According to the data, refinance accounts for 65% of all stated reasons for obtaining a commercial loan. In these cases, no actual transaction prices are available to loan originators. Moreover, even in a situation where the transaction values are available, the originator usually uses the appraisal value rather than the actual transaction value to calculate the LTV Ratio. These practices lead to more dependence on the appraisal value. Any distortion in appraisal value could lead to substantial financial gains for both borrowers and originators in terms of lower interest rate and easier securitization, respectively.

By comparing commercial and residential mortgages, I am able to identify several factors supporting my claim that there may have been large scale misreporting in the commercial mortgage origination process.

1. Conflicting incentives and an asymmetric information problem induced by securitization are similar to RMBS.

2. Some of the originators and underwriters who were found responsible for RMBS misreporting were also involved in the origination and securitization process in CMBS.

3. The property value appraisal process and other origination procedures for commercial loans utilize more subjective information compared to residential mortgages. Thus, this opacity provides space for misreporting, and meanwhile, it makes potential misreporting difficult to identify.

Additionally, several reasons explain why large scale misreporting has less of a likelihood of occurring in the commercial mortgage origination process.

1. Commercial mortgage borrowers are commonly enterprises and residential mortgage borrowers are commonly individuals. Enterprise may potentially have more discipline in reporting.

2. The average size of a commercial mortgage is much bigger than a residential mortgage, and there are, on average, fewer loans in CMBS compared

to RMBS. Thus, more scrutiny and supervision may be paid to each property from investors, rating agencies, and other market participants.

3. Prior to the crisis, there were less price appreciation and volatility for commercial properties compared to residential properties.

Several obstacles make it difficult for researchers to study and identify potential misrepresentation and other types of wrongdoing in the financial industry. These obstacles include data availability and information timeliness. As a consequence, existing literature in forensic finance is often about topics where fraudulent activities have already been reported and discovered. Meanwhile, as researchers, we also have certain advantages over other parties in discovering potential fraudulent activities. First, we usually have a less-biased, ex-ante opinion compared to other parties who are often financially tied to the findings. Second, we have the ability and necessary tools to study these subjects with large scale data in hypothesis testing settings.

1.3 Data

The data for this paper mainly comes from Bloomberg Professional. Bloomberg has deal level data, tranche (bond) level data as well as loan (property) level data for CMBS. Deal level data includes average Loan-to-Value (LTV) ratio, average Debt-Service Coverage Ratio (DSCR), original balance, weighted average coupon (WAC), average amortization speed, number of loans, and other aggregate deal level information. For tranche level data, Bloomberg has tranche balance, credit support, rating history, and other tranche-specific information. Loan level data is categorized into three types. First, Bloomberg has information for the loan/property at origination. Such information includes loan balance, loan term, amortization schedule, coupon schedule, Underwritten Net Operating Income (UW NOI), LTV, DSCR appraisal value, and other static information such as address and type of the property. Second, Bloomberg also contains the current information of the loan such as loan status (e.g., delinquency, prepaid, defeased). Third, the loan level data contains the time series of the financial information such as NOI, revenue, expense, and occupancy rate, which are extracted from the monthly trustee report. This information is generally available until the loan is terminated.

Bloomberg in general has good coverage on the data although a significant amount of deals are missing loan level information. In my observation, the following main reasons account for Bloomberg's lack of the loan level data. First, Bloomberg has relatively poorer coverage for older vintages. Second, Bloomberg has low coverage CMBS deals that are private placements. Private placement securities are not regulated by the SEC to release deal quality information to public. For a certain amount of CMBS that have deal, tranche, and some loan level data coverage, Bloomberg does not have coverage for a time series of financial variables and so this does not allow me to perform certain analyses.

1.3.1 Variable Description

The following loan characteristics are used in regression analysis to control for the risk of the loan.

Loan-to-Value (LTV) ratio and Debt-Service Coverage Ratio (DSCR): These two variables are considered the most important predictors for mortgage default. According to publicly available rating criteria, both variables are important inputs in CMBS rating models. LTV ratio reflects the difference between initial loan balance and the appraisal value of the property. The lower the ratio, the stronger the ability for the loan to sustain a decline in the property value. In case of default, LTV ratio also determines the recovery rate after a foreclosure. Unlike residential mortgages, for which property values are determined by actual transaction prices in most cases, appraisers generally determine the value for commercial mortgages. Moreover, due to the nature of commercial property, the appraisal process often involves more judgment and "soft" information about the property. This potentially leaves more room for borrowers and originators to shop for a high valuation. DSCR compares the net cash flow for the property to the debt payment. A higher DSCR ratio suggests that the property has more net cash flow compared to debt service.

Loan Size: This is measured by the original balance of the loan. Loan size may affect the level of supervision and scrutiny from investors and rating agencies. Loan size potentially relates to the default probability.

Cutoff Coupon/Spread: Most CMBS loans are floating rate mortgages.

The spread is used to measure the view from the originator regarding the risk of the loans.

Term of Maturity: The typical terms of a commercial mortgage range from 10 to 30 years.

Amortization: Commercial loans are (mostly) not fully amortized at the end loan term. One common schedule for amortization is a 10/30 schedule: the loan matures in 10 years but the amortization is based on 30 years. Thus, at the end of the loan term, there is a substantial amount of unpaid principle. Before the financial crisis, an increasing amount of loans had very slow or no amortization (interest only loans). In this chapter, I categorize commercial mortgages in CMBS into three groups: interest only or balloon loans (zero or negative amortization), partial interest only (some but not full amortization), and full amortization loans. I include the fixed effects for these categories of amortization speed into all regressions.

Number of Properties: A small portion of loans contain multiple properties. The diversification effect may affect the risk of the loans.

Property type: Loan performance may vary across different types of properties. In this paper, I categorize commercial properties into five main types following the industry convention: office, retail, hotel, industrial, and multifamily.[6]

[6]There are more than five categories according to the code in Bloomberg. All other property types are included in the “industrial” type.

1.3.2 Sample Selection

The data covers CMBS issued from 1990 to the end of 2013. Data coverage between 1990 and 1994 is scare so I mainly focus on post-1995 CMBS deals. Since results are sensitive to the economic and real estate downturn, I limit my main analysis to pre-2006 deals to avoid the impact from the financial crisis.

There are 96,184 loans in the main sample. Among them, 76,018 loans have loan characteristics and a certain time series of financial information for analysis. Finally, there are 39,276 loans with the realized NOI available at the end the origination year.

Table 1 shows the summary statistics for the delinquency along with other loan characteristics for the main sample.

1.4 Net Operating Income

Underwritten Net Operating Income (UW NOI) is the most important financial variable for a commercial mortgage. Since a borrower for a commercial mortgage is commonly an independent entity, the cash flow from the property will be the sole source for debt service. The UW NOI also serves as a key input for the commercial property appraisal process following Equation (1.1).

$$PropertyAppraisalValue = \frac{UWNOI}{CapitalizationRate} \tag{1.1}$$

The appraiser usually derives the applicable capitalization rate from the market capitalization rates for similar properties in that area. Certain adjustments are made according to property conditions and other factors. Fixing the capitalization rate, the appraisal value is proportional to UW NOI. The appraisal value is used to calculate LTV ratio, which is one of the most important risk measures. A higher appraisal value helps a borrower be eligible for a larger loan balance as well as a lower interest rate.

Following Equation (1.2), the UW NOI also goes into the calculation of DSCR, which is another key measure for the risk of a loan. Other loan characteristics such as debt yield are also directly or indirectly determined by UW NOI.

$$DSCR = \frac{UWNOI}{DebtService} \tag{1.2}$$

However, for this particularly important variable, the borrower and loan originator have flexibility with regard to reporting of the variable. In general, the UW NOI is the best estimation for the upcoming NOI for the property. The following paragraph is a quotation from the prospectus of a CMBS deal (deal ticker: CAMC 2002-CAM2).

““Underwritten Net Operating Income” or “U/W NOI” means, with respect to any Mortgaged Property, an estimate of the total Net Operating Income anticipated to be available for annual debt service on that Mortgage Loan, calculated as the amount of Underwritten Revenues minus Underwritten

Expenses, before considering any reserves, capital expenditures or leasing costs. The amounts shown on the schedule generally reflect the estimates made by the related Originator in conducting its underwriting in connection with its origination of its Mortgage Loans."

1.4.1 How does the UW NOI compare to Realized NOI?

At the end of each calendar year for the life of a CMBS deal, the trustee of a CMBS deal issues a trustee report, which documents all the ongoing information including the realization of NOI for the past year. I utilize the realized NOI to compare with the UW NOI by computing the relative difference following Equation (1.3). More specifically, for realized NOI, I use the NOI of the origination year for my main analysis. In the robustness test, I also use NOI for the year following the origination year since the NOI of the origination year is missing for about half of the loans.

$$OverEstimation = \frac{UWNOI - RealizedNOI}{UWNOI} \tag{1.3}$$

Figure 1 shows the distribution of Over-estimation of NOI for all loans originated between 1995 and 2006 with available data. I skip the 2007 and later vintage because, as previously mentioned, I want to avoid the adverse impact from the financial crisis on the realized NOI. Figure 1 shows the distribution of over-estimation has a positive mean and skews to the right. This suggests that borrowers and originators, on average, overstated the UW NOI even during the booming period prior to the crisis. The UW NOI is inflated by, on average, 4.8% compared to realized NOI.

1.5 What Causes the Over-estimation of NOI?

In the previous section, I showed, on average, that UW NOI was consistently over-estimated prior to the financial crisis. It is important to understand that the realized NOI at origination year is an ex-post measure. Thus, it could be affected by many post-origination random shocks such as variation in rent, occupancy rate, and operating expense. The natural question to ask would be whether the over-estimation is caused by an unexpectedly low realization of NOI (the null hypothesis), or the biased initial estimation (the alternative hypothesis). An unexpectedly low realization of NOI occurs when the economy, more specifically, the commercial real estate market, performs worse than what is expected by borrowers and originators (for example, an adverse economic condition leads to low rent and a high vacancy rate). The second situation, the alternative hypothesis, is more problematic since it involves false representation of the asset's important financial information. According to the statement in the CMBS prospectus, the UW NOI is supposed to be an unbiased estimation produced by the best efforts of loan originators.

In this section, I lay out five hypothesis testings in order to distinguish these two alternative explanations for NOI over-estimation.

1.5.1 Time Series of Over-estimation

Hypothesis 1. *With only an unexpectedly low realization of NOI and an unbiased estimation of UW NOI, the over-estimation is positive only when there is a negative shock in realized NOI. Therefore, positive over-estimation should occur when the economy and, specifically, the commercial real estate market, experiences negative shocks with respect to NOI.*

The over-estimation is the percentage difference between UW NOI, which is the esimated NOI based on the best effort provided by the borrower and the originator. The realized NOI is affected by the general economic condition in the commercial real estate market. The latter is sensitive to changes in occupancy rate, rental rate, and property maintenance expense among other random factors. If the over-estimation is mainly caused by the low realization of NOI, we should expect positive over-estimation to occur when the real estate market faces negative shocks and negative over-estimation to occur when the real estate market faces positive shocks.

Table 2 documents the over-estimation for loans originating between 1997 and 2013. Figure 2 presents the time series of over-estimation and the annual change of realized NOI. The realized NOI change is calculated by aggregating the annual NOI for outstanding properties when the NOI of last year and current year are both available. The bar chart demonstrates the annual issuance of the CMBS.

Several important observations can be gleaned from Figure 2. First, the average over-estimation was close to zero during the period between 1997-2002 and it rose sharply after 2003, peaking in 2006 at about 11%. Then very few loans originated in the 2008 and 2009 period and, after the financial crisis, the average over-estimation has been relatively low. Second, before the inception of the crisis, the annual change in realized NOI based on the existing properties in CMBS had always been positive with only one exception of minor negative value. During the period when the market experienced very significant over-estimation of NOI (2003-2007), the commercial real estate market performed well. Figure 3 presents the distribution for each sub-period.

While the annual change in realized NOI presents a good reflection of the economic condition of the commercial real estate market, the hypothesis testing requires a comparison between the over-estimation and "economic shocks." In unreported results, I lay out an array of measures on "economic shocks," which are calculated by the difference between the consensus and realized value for key macroeconomic and real estate related indicators (e.g., home price index, retail sales, jobless claims, GDP growth rate). In unreported results, I document that, during most of the period from 2003-2006, the realized values were mainly better than the consensus values. This provides further evidence that the over-estimation did not coincide with adverse economic shocks.

The implication of the results for Hypothesis 1 is clear. The fact that significant positive over-estimation of NOI occurred during the period of good commercial real estate performance rejects the null hypothesis. The years with substantial over-estimation, interestingly, coupled with the booming period of MBS and the period when mis-reporting in RMBS is found to be prevalent.

1.5.2 Originator Heterogeneity

Hypothesis 2. *With only an unexpectedly low realization of NOI and an unbiased estimation of UW NOI, the over-estimation should not be related to the originator of the loan after controlling for loan characteristics, origination timing, and location of the property.*

If the over-estimation is only caused by low realization of NOI and the estimation is initially unbiased, the over-estimation should be unrelated to originator especially after controlling for loan characteristics. The rationale behind this hypothesis testing is that the random estimation errors made in different loans cancel out each other out so the average over-estimation by originators is close to zero. **?** show that originators played a central role in misreported second lien residential mortgages. In this section, I try to study the cross-sectional differences in over-estimation of NOI among originators. I focus this part of analysis on those originators that have at least five hundred loans between 1995 and 2006 with available data; in total, eighteen originators satisfy this condition.

Table 3 shows the summary statistics for over-estimation of NOI by originators. Table 3 is sorted by the mean of over-estimation. The most important observation from Table 3 is that large cross-sectional differences existed among originators. The average over-estimation was as high as 16%

for LaSalle while Principle Commercial Funding had the lowest over-estimation of -3%. All originators save three overstated the NOI during the sample period. The right tail mainly contributes higher-than-zero mean since the distributions of over-estimation are generally skewed to the right. The rank of mean is very similar to the rank of 75 Percentile.

In order to formally test Hypothesis 2, regression analysis is performed to control for the loan characteristics related to over-estimation along with time- and location-fixed effects following Equation (1.4).

$$\begin{aligned} OverEstimation_i = \alpha_0 + \gamma Controls_i + OriginatorFEs \\ + YearQuarterFEs + StateFEs + \epsilon_i \end{aligned} \tag{1.4}$$

Figure 4 shows the results between average over-estimation and the coefficients of the originator fixed effects. The result confirms the rejection of Hypothesis 2 with 7 out of 18 originators having significant fixed effects (BOA is the reference originator). The coefficients are highly correlated with the mean of over-estimation by originators.

1.5.3 Was the Over-estimation Affected by Incentives?

Hypothesis 3. *With only an unexpectedly low realization of NOI and an unbiased estimation of UW NOI, the over-estimation should not be related to the LTV ratio, DSCR, and other variables linked with the marginal benefit of inflating UW NOI.*

If the over-estimation is only caused by the unexpectedly low realization of NOI and the estimation is initially unbiased, the degree of over-estimation should not respond to the marginal benefit of inflating the UW NOI. Risky loans—for example, loans with a high LTV ratio and a low DSCR—benefit more from a marginal change in UW NOI through two channels. First, interest rates charged to borrowers are usually more responsive to changes in LTV and DSCR when these two variables indicate the loans are risky. Second, when originators sell loans to CMBS issuers, the prices of mortgages are mostly affected by LTV and DSCR when these two variables are near securitization cutoffs.

Table 4 shows the regression result for over-estimation on LTV, DSCR, and other loan characteristics following Equation (1.6).

$$\begin{aligned} OverEstimation_i = \alpha_0 + \beta_1 LTV_i + \beta_2 DSCR_i + \gamma Controls_i \\ + YearQuarterFEs + StateFEs + \epsilon_i \end{aligned} \tag{1.5}$$

I examine the impact of LTV ratio in Model (1), the impact of DSCR in model (2) and jointly in model (3). Loans with high LTV appear to have significantly higher over-estimation while the impact from DSCR is not significant. It is also notable that larger loans, loans with higher coupons, floating rate loans, loans with partial or no amortization, and multifamily properties tend to have higher over-estimation.

To further verify the relationship of over-estimation and LTV/DSCR, kernel regressions of over-estimation on LTV and DSCR visualize the results. Figure 5 shows the plot for the non-parametric analysis regarding LTV. The over-estimation increases with the LTV from negative to more than 7%. The result is consistent with the incentive argument: for a high LTV loan, the marginal benefit of getting higher appraisal value through over-estimated NOI is high to both borrowers and originators. Figure 6 shows the results for DSCR and the result is consistent with the incentive to over-estimate NOI. More risky loans with lower DSCR have higher over-estimation. In sum, the results presented in this section reject the null Hypothesis 3.

1.5.4 Has the Over-estimation Been Affected by Securitization Threshold?

Hypothesis 4. *With only an unexpectedly low realization of NOI and an unbiased estimation of UW NOI, the over-estimation should not respond to securitization thresholds in LTV and DSCR.*

Securitization thresholds are certain values for risk measures of a loan. These particular values are often round numbers and the pricing as well as securitization of mortgages are often sensitive to whether the risk measures fall above or below certain thresholds. For example, FICO score 640 is one example of the threshold for residential mortgage. A lower than 640 FICO score makes mortgages subprime and subprime mortgages face a different pricing and securitization category. For commercial mortgages, 5-unit LTV (such as 75% and 80%), and DSCR (such as 1.20 and 1.25) values are important thresholds. For LTV ratio, loans at or just below the thresholds are deemed to substantially safer, compared to loans just above these thresholds. Sensitivity to thresholds is driven by the rating matrix used by major rating agencies. Publicly-available rating criteria shows that the rating matrix is commonly based on 5-unit round numbers.[7] This creates a strong incentive for originators and borrowers to make loans to meet these thresholds.

With the benefits for loans reaching these 5-unit thresholds, it is expected that there will be a large amount loans clustering at these values. Figure 7 confirms the clustering and it further shows the potential spikes of over-estimation at the threshold. In unreported results, DSCR thresholds assemble a similar pattern.

In order to formally test whether the distributions of over-estimation are different at 5-unit LTV and DSCR thresholds compared to loans that are off the thresholds, I draw the distribution and run a Kolmogorov-Smirnov test. Figures 8 and 9 present the results for LTV and DSCR, respectively. The distribution for over-estimation at the thresholds skewed to the right for both LTV and DSCR. The Kolmogorov-Smirnov test shows that the over-estimation of loans at thresholds are more positive than other loans and the p-values are 0.000 and 0.013, respectively, for LTV and DSCR.

1.5.5 Is Over-estimation Priced in by Originators?

Hypothesis 5. *With only an unexpectedly low realization of NOI and an unbiased estimation of UW NOI, the over-estimation should be unrelated to the interest rate paid by borrowers.*

[7]For example, the S&P's "Rating Methodology And Assumptions For U.S. And Canadian CMBS" is available through this link. `https://www.standardandpoors.com/prot/ratings/articles/en/us?articleType=HTML&assetID=1245380021782`

If the UW NOI is an unbiased estimate, the lender should not know or have any ability to predict the future trend of the cash flow at the origination. Thus, the pricing of the loan (interest rate charged to borrowers) should not be related to the over-estimation. Following Equation (1.6), I perform a regression analysis with origination interest rate (coupon or spread) as a dependent variable on the over-estimation of NOI along with loan characteristics, location, and time fixed effects.

$$\begin{aligned} InterestRate_i = \alpha_0 + \beta_1 OverEstimation + \gamma Controls_i \\ + YearQuarterFEs + StateFEs + \epsilon_i \end{aligned} \tag{1.6}$$

Table 5 presents the results and offers several very interesting observations. In Model (1), the regression includes samples with all originators. The results suggest that the over-estimation has a positive and significant impact on the interest rate of the loan. This indicates that the originators knew the loans were more risky than other loans, which led them to charge borrowers higher interest rates. In order to verify whether all originators behaved in the same way, I run the regression on the sub-sample based on originator fixed effects on over-estimation from previous section. Model (2) only includes loans with significantly positive fixed effects for over-estimation ("bad" originator) and Model (3) includes the rest of the loans ("good" originator). The coefficient for these "bad" originators goes up, and meanwhile, the coefficient for these "good" originators is no longer significant. One interpretation for the results is that a "bad" originator knows an ex-ante over-estimation exists but the "good" originator does not know. The results further verify the rejection of the null hypothesis.

Combining the results with the heterogeneity of over-estimation in originators, reasonable suspicion is made about the question of whether certain originators systematically reported biased (inflated) UW NOI to make their issued mortgages more attractive to investors. In the next section, I further study the relationship between over-estimation and loan performance at the originator level.

1.6 Does Over-estimation of NOI Affect Loan Performance?

During the test for Hypothesis 2, I show the existence of large cross-sectional differences in both over-estimation of NOI. In this section, I combine that with loan performance and evaluate in detail how over-estimation affects loan performance.

1.6.1 Large Cross-sectional Differences in Loan Performance among Originators

Significant variations are found in the loan performance for mortgages securitized from 1995-2006. For the same group of originators that have at least 500 loans with available NOI data, the severe delinquency percentage ranges from 3% (Wells Fargo) to as high as 15% (LaSalle).[8]

[8] There are originators with a higher average delinquency rate such as EMAC (21.9%). This originator, along with others, is excluded in the regression analysis because the time series of NOI data is not available.

In order to get a clear picture about the performance difference, regression analysis is performed to study the originator fix effects with respect to delinquency, controlling for loan characteristics, time, and location fixed effects following Equation (1.7). Figure 10 shows the plot between the average delinquency rates and the coefficients of originator fixed effects from the regression. They are highly correlated (correlation is 0.75). The triangle markers indicate that the fixed effects are significant at a 5% level.

$$\begin{aligned} Delinquency_i = \alpha_0 + \gamma Controls_i + OriginatorFEs \\ + YearQuarterFEs + StateFEs + \epsilon_i \end{aligned} \tag{1.7}$$

1.6.2 Type of Originators

Several studies focus on the connection between the type of commercial mortgage originator and loan performance as well as pricing. **?** show that loans originated by conduit lenders have a lower risk adjusted spread compared to portfolio lenders. **?** show that loans originated by commercial banks, insurance companies, and finance companies have better performance compared to loans originated by conduit lenders and foreign entities. In Figure 11, the top three originators with high over-estimation (LaSalle, CIBC, and German American) are all foreign entities and this aligns with the worst performing originators documented in extant literature.

1.6.3 Summary Analysis

In this section, I present and discuss two figures that show the relationship between over-estimation and delinquency aggregated by originators. Figure 11 plots the average over-estimation and probability of delinquency by originators. Figure 12 plots the coefficients of originator fixed effects from regression on loan characteristics with over-estimation and delinquency as dependent variables, respectively. Several observations are of further explanation. First, both originator fixed effects have significant variation among each other. Average over-estimation by originators ranges from -3% to 16% and average delinquency by originators ranges from 3% to 15%. Second, average over-estimation and delinquency at originator level are highly correlated. The over-estimation of NOI seems to have a direct impact on originator loan performance. Third, the coefficients of originator fixed effects tell us that, even after controlling loan characteristics, state fixed effects, and quarter fixed effects, both over-estimation (ranging from -2.7% to 8.2%) and delinquency (ranging from -0.9% to 4.69%) still have large cross sectional differences. Moreover, the correlation between fixed effects remains strong.

1.6.4 Regression Analysis

The previous section documented a clear correlation between originator level over-estimation and delinquency. In this section, I quantify the magnitude of the impact of bias in UW NOI on loan performance. The obstacle is to separate the bias in estimation of UW NOI from the over-estimation caused by randomness in the realized NOI. Here, I assume that the variations in over-estimation within originators all attribute to bias in estimation for the following reason: aggregating on an originator level and requiring each originator to have at least 500 loans ensure that randomness in the realized NOI is cancelled out. In other words, I want to capture the effect from the ex-ante biased estimation of UW NOI rather than the ex-post "unlucky" poor realized cash flow outcome.

I perform a logistic regression with the delinquency status as the dependent variable to study the impact of over-estimation on delinquency following Equation (1.8). Delinquency is an indicator variable that equals 1 if the loan is delinquent for 90 days or more, in foreclosure, REO, default.

$$\begin{aligned} g(Delinquency_i) = \alpha_0 + \beta AvgOverByOrig + \gamma Controls_i \\ + YearQuarterFEs + StateFEs + \epsilon_i \end{aligned} \tag{1.8}$$

g(.) is the inverse of logistic function.

Models (1) and (2) in Table 6 show the results baseline model without over-estimation. All samples with loan characteristics data available are included in Model (1). Only samples whose originators have 500 or more loans are included in Model (2). Comparing Model (1) and (2), the relationship between delinquency status and loan characteristics are similar across two samples. In general, loans with higher LTV, lower DSCR, higher loan balance, higher coupon rate, fixed interest rate schedule, loans with multiple properties, and slower or no amortization are more likely to be delinquent. The directions of these impacts generally align with my expectations.

The result in Table 6 Model (3) shows each 1% increase in average over-estimation makes the loan 20% more likely to become seriously delinquent. Illustrating the magnitude of impact by two originators in our sample, the difference in average over-estimation between LaSalle and Principle Commercial Funding are 19% (16% and -3%); the discrepancy in over-estimation translates to the observation that LaSalle's loans are 380% (2000*0.19) more likely to be delinquent than Principle Commercial Funding's loans. The predicted difference in delinquency rates explains most of the difference in actual delinquency: LaSalle: 15.2% vs. Principle Commercial Funding: 3.3% (460% higher likelihood).

The surprisingly high impact on delinquency from originator level over-estimation hints at the existence of other potential reporting also tied to originators. Due to data limitations, I am not able to examine all potential misreporting.

1.7 Discussion

1.7.1 Were Over-estimations Priced Sufficiently?

In the section where I tested Hypothesis 5, the results showed that each 100% of over-estimation will increase the interest rate of the loan by 7 to 9 basis points after controlling for loan characteristics and fixed effects. It is natural to think about the question of whether the difference in interest rate is sufficient to compensate for the extra risk brought on by the over-estimation of UW NOI. If the answer is yes, the misreporting is less of an issue since the investors of the mortgage, essentially the buyers of the CMBS, get fair compensation for the additional risk. If the answer is no, it is a meaningful empirical question to examine the magnitude of the losses suffered by the investors in terms of the interest payment. **?** show that the RMBS investors were not fully compensated for the additional risk from misreporting in residential mortgage.

I tackle the question through the following steps. First, I run a regression to examine the impact from over-estimation on delinquency; I then determine how much incremental delinquency brought was by a 10% (a arbitrary number as an example) over-estimation through this step. Second, I set an example of a "representative loan" with 67.1% for LTV and 1.72 for DSCR. Hypothetically, if the UW NOI of the loan is not inflated by 10%, the "corrected" LTV and DSCR changes to 73.81% and 1.56, respectively. Third, I derive the "fair" compensation in terms of additional interest rate according to a regression of interest rate on LTV, DSCR, and other loan characteristics. Finally, I compare the "fair" compensation to the actual difference in interest from the previous procedure.

Table 7 shows the regression results related to previous steps. The changes in LTV and DSCR caused by inflated WU NOI (for 10%) demand two basis points compensation in interest rate paid to investors. Compared to the actual difference in interest rate difference, which is merely 0.7%-0.9%, investors are far from fully-compensated for the additional risk related to the over-estimation.

1.7.2 Does Over-estimation Affect CMBS Ratings?

One distinction between the CMBS and RMBS credit rating process is that the CMBS rating process involves more soft information and subjective opinion than the RMBS rating process. According to public rating criteria obtained from the Moody's, S&P's, and Fitch websites, all CMBS rating processes involve a revaluation of the appraisal value. To be more specific, rating agencies derive their own property values[9] by consolidating information from on-site visits, property specific research, proprietary capitalization rate models, and other information. The rating agencies may also adjust an originator's reported UW NOI following their own accounting standards and related criteria. The rating models use their adjusted property value instead of the original property value provided by the originator as final inputs for rating models.[10] Thus, with the additional private information and evaluation procedures, the rating agencies can potentially add value to the securitization process by giving lower credit ratings to deals with high over-estimation.

Following other academic research, I use the AAA subordination level– the percentage of the deal receiving non-AAA rating—as a measure for the credit rating of a deal.[11] I first need to show that there are substantial differences in aggregate over-estimation among deals. In unreported results, the

[9] It is called S&P's value for example.

[10] One public criteria released by Moody, notes the average adjustment is -20% compared to the original appraisal value.

[11] When calculating the AAA subordination level, if there is a rating disagreement among credit rating agencies, the highest rating is used.

standard deviation in deal level over-estimation is 13.2%. One word, the deal level delinquency is affected by the deal level over-estimation.

I test for the relationship between average over-estimation by deal and AAA subordination level following Equation (1.9). The variable of interest here is β_1. Year fixed effects are included in all specifications to control for the potential changes in market view, economic conditions, and rating criteria.

$$\begin{aligned} AAASubordinationLevel_i &= \alpha_0 + \beta_1 AvgOverbyDeal_i \\ &+\gamma Controls_i + YearQuarterFEs + \epsilon_i \end{aligned} \tag{1.9}$$

Table 8 shows the results for the regression analysis. Model (1) shows that the base line regression result, which only includes the deal characteristics, and the direction of coefficients are generally aligned with our expectation. Model (2) shows the result with deal level over-estimation and it also shows that the over-estimation does not have a significant impact on AAA subordination level. This suggests that all evaluations performed by the rating agencies on the properties failed to capture the potential over-estimation, and thus, the ratings are not affected by the aggregate level of over-estimation. Due to concerns for low coverage on over-estimation, in Model (3), I compute the over-estimation based on NOI on the following year instead of the origination year. The average availability of the data increases from 52% to 72%. The result remains the same.

1.7.3 Robustness Check

In unreported results, I perform (but am not limited to) the following robustness checks.

First, for calculation of over-estimation, I use the realized NOI one year after origination year; this gives me a substantially larger sample. Main results hold with the same revised measure. Second, I exclude newly-built properties from the regressions because historically NOI are not available to originators and borrowers, and thus, the UW NOI are harder to estimate. The properties built with two years before origination contribute to less than 5% of the whole sample and eliminating them from the main sample does not significantly change results. Third, I adapt finer aggregations for location and property type fixed effects in main regressions and the results hold.

1.8 Conclusion

Asymmetric information and adverse selection problems are the key features in the structured finance market. Investors evidently have little capability and intention to perform due diligence to examine property level information in mortgage-backed securities, especially when the securities do well. Even after the financial crisis, little has been done to change the structure of the market, Additionally issuance of CMBS quickly rose to its pre-crisis level.

In this Chapter, I examine the Underwritten Net Operating Income (UW NOI) and other key financial variables for securitized commercial mortgages. Before the financial crisis, the UW NOI was consistently overstated by 7.8%. This overstatement lead to LTV being misreported as 67.1% from 84.2% and DSCR as 1.72 from 1.59. For the top seven-out-of-eighteen originators with at least 500 data available, the average over-estimation is 10.7% from 2003-2007. I then use five hypotheses testings to distinguish two competing explanations for the over-estimation: an unexpectedly low realization of NOI against biased UW NOI estimation. By showing evidence for the timing of the over-estimation, cross-sectional differences in originator level over-estimation, relationship between over-estimation and marginal benefit of inflating NOI, responses of over-estimation to securitization thresholds, and impact of over-estimation on initial interest rate, I reject the null hypotheses and conclude that the over-estimation in UW NOI is at least partially caused by biased estimation.

The over-estimation of UW NOI by originators appears to explain most of the cross-sectional differences in loan performances after controlling for loan characteristics, location, and time fixed effects. Substantial cross-sectional differences in both average over-estimation and delinquency by originators exist and these are highly correlated. The logistic regression analysis suggests that each 1% increase in an originator's over-estimation level leads to a 20% relative increase in delinquency probability. I also examine the role of rating agencies with respect to the over-estimation. It appears that the AAA subordination levels do not respond to the deal level over-estimation. Rating agencies fail to add values for investors through their credit ratings.

Chapter 2

Identification and Estimation of Strategic Credit Rating

2.1 Introduction

Rating agencies play a central role in the structured finance market. They have largely been blamed for the recent financial crisis for failing to give credit ratings that correctly measured the default risk of security. Due to the complexity of the structured finance products and regulatory capital requirements, a majority of investors—including sophisticated institutional investors such as pension funds and insurance companies—rely heavily on credit ratings published by credit rating agencies for their investment decisions. Rating inflation has been recognized as a major cause of the 2008 financial crisis by recent studies, including, for example, **?** and **?**. Peer effects have been documented as the major concern for the conflict of interest in the credit rating business model wherein credit rating agents compete with their peers for rating business while their revenues mainly come from the issuers whose financial products are getting rated.[1]

[1] Two practical channels of peer effects have been discussed in the literature: that is, rating shopping (see for example, **???**) and rating catering (see for example, **???**).

In this chapter, I investigate rating agencies' behaviors by using a strategic interaction model and a dataset for Commercial Mortgage-Backed Security (CMBS), originated before and after the 2008 financial crisis. Residential Mortgage-Backed Security (RMBS), Commercial Mortgage-Backed Security (CMBS), and Collateral Debt Obligation (CDO) all suffered tremendous losses during the financial crisis.[2] CMBS tranches initially granted with high investment grades have experienced large scale downgrades (about 10 notches on average) and defaults,[3] so too have RMBS and CDO securities.

Following the literature, our empirical study focuses on non-agency CMBS.[4] The CMBS is a more attractive segment of the structured finance market than RMBS and CDO to study the credit rating behaviors before and after the financial crisis. The first advantage is that CMBS issuances have largely recovered to their pre-crisis levels while (non-agency) RMBS and CDO markets are at a small fraction of their pre-crisis levels.[5] Second, the structure and risk profile of the underlying assets of CMBS deals issued after the

[2]Note that CDO specifically refers to CDO with mortgage–backed security as the main underlying assets.

[3]A CMBS (or CMBS deal) is a large package of tranches backed by the same group of commercial mortgages. A CMBS tranche is one piece of the securities offered in a CMBS deal.

[4]Agency CMBS are issued by government-related entities such as Fannie Mae and Freddie Mac. These securities have different risk profiles compared to non-agency Mortgage-Backed Security and usually have an implicit or explicit guarantee on payments by the federal government.

[5]According to data from Bloomberg, at the peak (i.e. 2006) before the crisis, the number of CMBS, RMBS and CDO issued are 139, 1864 and 502, respectively. In 2013, the number of CMBS, RMBS and CDO issued are 124, 120 and 8, respectively. Re-securitized RMBS are not counted.

financial crisis have generally remained the same as before the crisis, except for some improvements in risk measures. In contrast, the underwritten criteria for RMBS have tightened with improved scrutiny on borrowers' soft information (such as income documentations), which are not observable to the researcher. Changes related to unobservable soft information make it difficult to compare RMBS deals issued before and after the crisis even with all possible observable loan risk characteristics. Moreover, the rebound in the CMBS market also provides us with sizable post-crisis CMBS deals.

Peer effects play an important role in credit agencies' rating behaviors, see (e.g. **????**, for the theoretic side). In our data, direct evidence exists regarding strategic interactions in credit rating. First, most of the CMBS tranches in our sample receive multiple ratings from different agencies, but rating disagreements are surprisingly small. Before the financial crisis, the SEC only qualified to participate in the CMBS rating market; this number expanded to five after the crisis.[6] Figure 13 presents the percentage of rating disagreements by vintage. For CMBS issued before the crisis, on average only 6% have any rating disagreement. Even fewer disagreements exist among AAA rated tranches than those tranches with non-AAA ratings, where the former is the most important composition of CMBS deals. Based on small disagreements in Figure 13, it is hard to justify that the rating agencies perform independent and objective evaluations of CMBS deals, albeit all agencies claim

[6]The agencies are S&P, Moody's, Fitch, and DBRS. Kroll entered the market after the financial crisis.

they have their own proprietary rating models on CMBS according to the publicly available CMBS rating criteria.[7]

The second piece of empirical evidence for the existence of peer effects is described in Figure 14. Following the literature, we use the AAA subordination level to measure the average rating of a CMBS deal. The AAA subordination level is the proportion of tranches (bond) issued with a non-AAA rating, which determines how much losses the CMBS can sustain before a AAA tranche suffers any losses. Figure 14 shows the average AAA subordination level by vintage, which decreases significantly after the financial crisis. Prior to the financial crisis, the AAA subordination level remains low at about 15%; this suggests that, on average, 85% of a CMBS deal is granted a AAA rating. After the financial crisis, the AAA subordination level goes up dramatically to the 25% - 35% range. Meanwhile, the rise in subordination level is accompanied by an improvement in loan quality, which is measured by the average severe delinquency.[8] Such a phenomena suggests that the rating agencies shift from an inflated to a conservative rating equilibrium.

In extant literature, several studies explain the change in CMBS AAA subordination level; all of these articles focus on pre-crisis deals. For example, **?** study the determinate factors driving the AAA subordination levels. The

[7]For example, S&P's "Rating Methodology And Assumptions For U.S. And Canadian CMBS" is available through this link. `https://www.standardandpoors.com/prot/ratings/articles/en/us?articleType=HTML&assetID=1245380021782`

[8]Severe delinquency is defined as the sum of delinquency for at least 90 days, foreclosure and REO.

authors show that these levels have a weak relation with ex-post or ex-ante measures of credit risk and are mainly driven by factors not related to risk, such as supply and demand on securities, deal complexity, and issuer incentive. **?** mainly focus on the change in investors' demand for CMBS tranche with investment grades. They attribute the decline in AAA subordination level to the loosening of capital requirements following a regulatory change. That article also shows that the reduction in subordination level before the financial crisis has little to do with the change in risk characteristics of the underlying CMBS deals.

In this chapter, we model the CMBS credit ratings as strategic behaviors that reflect the peer effects from other rating agencies. We incorporate the interaction from other rating agencies through the estimation on market "beliefs" on the ratings. In our model, the beliefs are estimated separately before and after crisis controlling for risk characteristics. A significant shift (in both statistic and economic senses) before and after the crisis triggered the existence of multiple equilibria in the rating market. By including the strategic interaction term, we establish semiparametric identification and estimation of the interaction–based model. Our identification method follows the idea in a germinal paper by **?**. Specifically, we exploit the variations in beliefs before and after the US subprime mortgage crisis to identify the peer effects coefficient. We further estimate the structural model by a two–step procedure. By including peer effects, the fitness of our model has been significantly improved.

The remainder of this paper is organized as follows. Section 2 addresses the data and characteristics of a CMBS deal. Section 3 introduces our benchmark model and establishes the identification of the structural model using equilibrium shift before and after the financial crisis. We also provide empirical evidence for the equilibrium shift after controlling for risk characteristics. Section 4 proposes a two–step estimation procedure using the pooled cross-section. Finally, Section 5 reports the empirical results and Section 6 concludes.

2.2 Data

2.2.1 Sample Description

Data on CMBS deals come from Bloomberg. We focus on US non-agency CMBS deals issued between January 2000 and May 2014. For various reasons, some important characteristics are missing for a proportion of observations. For instance, private placement CMBS deals do not publicize detailed deal information, since this is not required by the SEC. We eliminate deals with missing risk characteristic information, which results in a final sample of 632 deals. Our sample covers about 51% of the 1,246 deals issued during the sample period. We classify deals issued in and after 2009 as post-financial-crisis issues, leading to 442 pre-crisis and 190 post-crisis deals.

Figure 15 presents the total number of deals issued and the number of deals included in our sample indexed by year. Clearly, dramatic changes are recorded in the CMBS market after the financial crisis. For example, in our sample, the number of deals issued dropped from 139 deals in 2006 to only

21 deals in 2008 and 22 deals in 2009. After the crisis, accompanied by a low interest rate environment and re-finance of matured loans, the CMBS deal issuance recovered to the pre-crisis level in 2013 with 117 issued deals.

2.2.2 Deal Characteristics

Table 9 reports the summary statistics of the AAA Subordination Level and CMBS deal characteristics in our sample. The AAA Subordination Level is the sum of the balances of non-AAA tranches divided by the total balance of the deal. It represents the maximum amount of percentage loss the deal can sustain before allocating any losses to a AAA rated tranche. Figure 14 shows the time series of average AAA Subordination Level by year of issuance (vintage). The subordination level had been steadily trending down before the financial crisis. The decrease in CMBS subordination level is almost 10% between 2000 (23.2%) and 2008 (13.5%), which implies that, on average, the CMBS deals issued in 2008 may sustain 10% less loss than 2000 deals. The AAA subordination level went back up after the financial crisis to more than 30% in 2013 and 2014, accompanied by fundamental changes in loan quality, as shown in the following paragraphs.

We use a host of deal-level characteristics in our CMBS rating analysis. The first two characteristics are loan-to-value ratio (LTV) and debt-service coverage ratio (DSCR). Table 9 shows that the pre-crisis deals are more risky in terms of LTV and less risky in terms of DSCR. These two variables are widely considered to be strong predictors of mortgage defaults for commercial mortgages. In particular, high LTV or low DSCR is related to risky commercial mortgage. Thus, we expect that a high LTV or a low DSCR relates to a high subordination level, all things being equal.

The third characteristic is the amortization schedule. Commercial mortgages, unlike residential mortgages, are mostly not fully-amortized (i.e. loan balance does not go to zero on maturity). In this case, borrowers need to pay full or partial principle at maturity, which leads to a higher default risk. **?** find that full-interest-only loans have higher default rates than partial-interest-only or fully amortized loans. We categorize commercial mortgages in CMBS into three groups: interest-only (no amortization at all), partial-interest-only (some but not full amortization), and full amortization loans. Table 9 shows the shares of full interest-only loans and partial interest-only loans. The share of fully amortized loans equals to one minus sum of these two former categories. More full interest-only loans exist pre-crisis, which suggests pre-crisis deals are more risky in this measure.

The fourth characteristic of interest is the number of loans. All things being equal, deals with a larger number of loans are less risky, and therefore imply lower subordination levels. The number of loans and effective number of loans derived from the Herfindahl index are used in rating models by credit rating agencies. As shown in Table 9, the number of loans are higher after the crisis.

The fifth characteristic is deal balance, defined as the original balance of the deal. **?** note that large deals tend to have more complex structures and worse performance. The average size of a CMBS deal is 1.5 billion USD; post-crisis deals are, on average, smaller.

The sixth characteristic is deal spread, defined as the difference between the weighted average coupon (WAC) of the deal and the 10-year treasury yield. The latter is deemed a risk-free interest rate. The spread will be positively related to the risk of the deal and it is expected to be positively correlated with subordination level. The spread is higher for pre-crisis deals, which suggests that these deals are more risky.

Finally, we consider property type to be a potential determinant of CMBS rating because, during the appraisal process, property type affects the capitalization rate. We categorize properties into five types: office, retail, hotel, industrial, and multifamily property. Typically, multifamily properties are viewed as the least risky while hotel and industrial properties are the most risky. As shown in Table 9, more office property and multifamily and less retail and hotel property loans are securitized after the crisis.

2.3 Model

A CMBS deal consists of a large group of mortgage assets, characterized by $x \in \mathbb{R}^d$. For any given CMBS deal, a credit rating agency chooses a percentage $p \in [0, 1]$, a proportion of the deal, to receive the top rating (AAA). For instance, suppose $p = 85\%$. Then, the 85% of the assets that have the lowest default risk in the tranche receive AAA. To decide on the percentage, an agency takes into account the characteristics of the deal x, his own private information ϵ, and potentially other agencies' ratings.

In this paper, we consider the following model to approximate an agency's choice

$$p = h^*(x, p^e, \epsilon) \tag{2.1}$$

where h^* is a (nonparametric) structural function and p^e is the market "beliefs" on the rating. A solution to (2.1) is a function: $p = p(x, \epsilon)$ that satisfies (2.1) with $p^e = \mathbb{E}(p(x, \epsilon)|x)$. Each solution constitutes an equilibrium. By the self-consistency of rational expectations (see for example, **?**), we have $p^e = \mathbb{E}(p|x)$ when there is a unique equilibria.[9] In the presence of multiple equilibrium (see for example, **?**), we have $p^e = \mathbb{E}(p|x, t)$ where t is the equilibrium selection mechanism to be introduced later.

The impact of p^e on p reflects the peer effects on the credit rating: a rating agency is inclined to choose a higher percentage given that all of her peers rate higher on similar mortgage assets. Due to such an effect, the credit rating agencies behave strategically while factoring in the expected market outcome. This type of econometric model was first suggested by **??** in the context of social interactions. In credit rating literature, **?** developed a theoretic credit rating model with regulation, where peer effects among credit agencies are modeled through the relative performance evaluation mechanism.

In Model (2.1), we use a nonparametric function h^* to model rating agencies' decisions. Regarding the empirical analysis of strategic behaviors,

[9] In this case, we can obtain market beliefs p^e by solving the nonlinear equation $p^e = \int_{\mathbb{R}} h^*(x, p^e, \epsilon) dF_{\epsilon|x}$.

nonparametric analysis has become central in economics for several reasons. First, game theoretic models on strategic interactions are usually silent on the parametric form of strategic effects. The introduction of additional parametric specifications, especially on the form of strategic effects, without careful justifications may lead to spurious identification and mislead empirical conclusions. In contrast, the general specification of (2.1) helps emphasize the role of an equilibrium shift on the identification of peer effects. For estimation, however, we will make additional parametric assumptions later for the purpose of simplification. Second, note that the dependent variable is a ratio between 0 and 1. It is well known that the usual linear specification is not proper for modeling limited dependent variables.

The empirical analysis of rating agencies' strategic behaviors using (2.1) involves two obstacles. First, the market "beliefs" p^e on the rating are not observed in the data. Second, the dependent variable p is limited to the interval $[0, 1]$. Since the former is a much deeper problem, we first deal with the latter in the following analysis.

We propose a transformation to the limited dependent variable, p. Without loss of generality, we let Φ be the CDF of the standard normal distribution.[10] Thus, (2.1) can be rewritten as

$$p = \Phi(h(x, p^e, \epsilon)). \tag{2.2}$$

[10]Another popular alternative is the logistic distribution function, $\exp(\cdot)/[1 + \exp(\cdot)]$.

where $h = \Phi^{-1}(h^*)$. Under the transformation, our model can be written as

$$\Phi^{-1}(p) = h(x, p^e, \epsilon)$$

for which the new dependent variable $\Phi^{-1}(p)$ is not limited. Note that our transformation technique is related to the so–called Box–Cox transformation literature (see for example, **?**). It is worth pointing out that our method is robust to the choice of the transformation function Φ. It is even possible to permit an unknown transformation function, but at the cost of complicating the arguments.

After dealing with the limited dependent variable issue, we introduce additional weak assumptions.

Assumption A (additivity)**.** *Let* $h(x, p^e, \epsilon) = \beta(x) + \alpha p^e + \epsilon$*, where* $\alpha \in \mathbb{R}$*,* $\beta : \mathbb{R}^d \to \mathbb{R}$*.*

Assumption B (mean independence)**.** *Let* $\mathbb{E}(\epsilon|x) = 0$*.*

Assumptions A and B are standard in empirical game literature. Specifically, assumption A requires that strategic effects from peers' credit rating behaviors can be represented by a constant coefficient α. A more general form of strategic effects is allowed (e.g., **?**) at the expositional expense. Assumption B is strong, but indispensable in econometrics literature.[11]

[11] It should also be noted that assumption B can be replaced by the quantile independence condition and then we can use the quantile regression approach for inference; see for example, **?**.

Under assumptions A and B, our model becomes

$$\Phi^{-1}(p) = \beta(x) + \alpha p^e + \epsilon, \tag{2.3}$$

with $\mathbb{E}(\epsilon|x) = 0$. **?** describes Equation (2.3) as a structure with the "reflection problem." Specifically, the market beliefs p^e on the right hand of the equation is given by the conditional distribution of p given x, while p as the dependent variable depends on p^e. This introduces a simultaneity issue.

2.3.1 Multiple Equilibria

Simultaneity might introduce multiple solutions to (2.3), that is, all the rating agencies simultaneously inflate their credit ratings, (2.3) remains to hold. Fix the value of x. Let $\mathscr{E}(x) \equiv \{p_1(x,\epsilon), \cdots, p_K(x,\epsilon)\}$ be the set of solutions that solve (2.3), where $K = K(x)$ denotes the number of equilibria. Thus, for $k = 1, \cdots, K$, Assumption B implies: each equilibrium solution $p_k(x,\epsilon)$ in $\mathscr{E}(x)$ needs to satisfy the following self-consistency conditions:

$$\mathbb{E}\big[\Phi^{-1}(p_k(x,\epsilon))|x\big] = \beta(x) + \alpha\mathbb{E}(p_k(x,\epsilon)|x). \tag{2.4}$$

In the following discussion, we show that the presence of the multiple equilibria and the non-degeneracy of the equilibrium selection mechanism are crucial for the empirical analysis of our model. Empirical evidence also shows the shift of the equilibrium before and after the U.S. subprime mortgage crisis.

2.3.2 Identification

Following **?** and **?**, the identification concept here is treated as the limit of statistic inference: given an infinite number of observations, can we recover the structural parameters α and $\beta(\cdot)$? If the answer is negative, then there is no hope to estimate α or $\beta(\cdot)$ using any finite sample. In our model, all of the information contained in an infinite sample is the conditional distribution $F_{p|x}$ of rating given the deal characteristics. We then wonder whether we can obtain α and $\beta(\cdot)$ from $F_{p|x}$? We consider our model to be identified if and only if the answer to this question is confirmed.

We now argue that α is not identified when there is a unique equilibrium, that is, for given distribution $F_{p|x}$ of observables, multiple values of the structural parameters $(\alpha, \beta(\cdot))$ that deliver the observed distribution $F_{p|x}$ exist. To see this, suppose the data come from one single equilibrium, either because of the uniqueness of the equilibrium, or the same equilibrium being selected all the time. Thus, we have $p^e = \mathbb{E}(p|x)$ which can be directly identified from the given distribution $F_{p|x}$. Difficulty arises when it comes to identifying α and β using variations in x, p^e and $\mathbb{E}\big[\Phi^{-1}(p)|x\big]$, since p^e is restricted to be fixed if x has been controlled for. Mathematically, our model implies one equation, Equation (2.4), but two unkonwns, α and $\beta(\cdot)$. One can show that any structure $\{\alpha, \beta(\cdot)\}$ is observationally equivalent to the structure with $\tilde{\alpha} = 0$ and $\tilde{\beta}(x) = \beta(x) + \alpha\mathbb{E}(p|x)$. Intuitively, we cannot distinguish the cases with and without peer effects: the rating agencies might take into account each other's ratings and the analyst explains the observed data perfectly well if he/she attributes all variations to the nonstrategic term, $\beta(x)$.

When there are multiple equilibria and different equilibria gets played at different time periods, we have an extra dimension of variation that gives multiple conditional distributions: $F_{p|x,t}$, where t denotes a time period. As a result, the nonstrategic term $\beta(x)$ itself is no longer able to explain all the data variations. Suppose different equilibria have been adopted by the credit rating market at $t = 0, 1$, where $t = 0$ and 1 denote before and after the 2008 financial crisis, respectively. With slight abuse of our notation, let $p_t(x, \epsilon)$ be the equilibrium strategy played for a given CMBS characterized by x at period t. Let further $p^e(x, t) = \mathbb{E}(p_t(x, \epsilon)|x, t)$. Therefore, we can specify our econometric model for equilibrium credit rating decision as follows:

$$p = p_t(x, \epsilon), \quad \text{for} \quad t = 0, 1; \tag{2.5}$$

$$\Phi^{-1}(p) = \beta(x) + \alpha\mathbb{E}(p|x, t) + \epsilon. \tag{2.6}$$

By (2.6), equilibrium beliefs $p^e(x, t)$ can still have variations even after we control for x. This is because from $t = 0$ to 1, the financial crisis has shifted the market equilibrium. The next lemma summarizes the above discussion.

Lemma 1. *We maintain assumptions A and B. Suppose for each x the data come from one single equilibrium. Then, the structural parameters α and $\beta(\cdot)$ are not identified. Moreover, suppose for some x the data come from two different equilibria before and after the financial crisis and $p^e(x, 0) \neq p^e(x, 1)$. Then α and $\beta(\cdot)$ are identified.*

Note that the identification rank condition $p^e(x, 0) \neq p^e(x, 1)$ is testable, since $\mathbb{E}(p|x, t)$ can be non-parametrically estimated.[12] The non-identification result in Lemma 1 is essential, which reflects the fact that all of the variations in the data are not sufficient to identify peer effects when the equilibrium does not change if we control for x.

Lemma 1 illustrates the extent to which the fully parametric estimation strategy is relying on the parametric structure for identification or merely for feasibility of estimation. Without equilibrium shifts due to the financial crisis, the estimation of peer effects in a fully parametric setting is misleading. For instance, one may consider a parametric version of our model: $\Phi^{-1}(p) = x'\beta + \alpha p^e_t + \epsilon$, where $\epsilon \sim N(0, 1)$. One could use maximum likelihood estimation approach to estimate coefficients $(\alpha, \beta')'$. Such an estimate, however, heavily relies on linearity and is not robust to even small model mis-specifications. In other words, one can not treat the linear-index specification simply as an approximation for simplicity of the inference.

Additionally, Lemma 1 also emphasizes the role of the multiple equilibria for empirical inference. Such an identification approach is first introduced in a germinal paper by **?** for identification and estimation of the sign of strategic effects. For such a reason, the non–linearity relationship between p and p^e in (2.3) is crucial for the identification of peer effects coefficient α. In contrast, **?** discussed some difficulties in the empirical analysis of peer effects in a linear

[12]We only need the rank condition hold for one value of x, not every x on its support. Such a rank condition is quite weak.

setting, which typically admits a unique equilibrium solution. Specifically, the reflection issue makes inference difficult to impossible. Because of this reason, the simpler linear specification is

$$p = \beta(x) + \alpha p^e + \epsilon,$$

which is not appealing if we observe multiple equilibria in the data.

2.3.3 Empirical evidence of multiple equilibria

Given the important role played by multiple equilibria in our identification strategy, we now present some empirical evidence for such an existence in the CMBS market during 2002-2014.

First, Figure 14 in the previous section shows significant increases in AAA subordination levels after 2008. For each CMBS, the AAA subordination level is defined as the proportion of the deal that receives a rating below AAA. By definition, the AAA subordination level of a deal i equals to $1-p_i$. Clearly, the AAA subordination level increases from about 15% to more than 30% after the crisis. The spectacular failure of the top-rated Mortgage-Backed Security raised investors' and regulators' attention to the inflation of credit ratings before the crisis. Consequently, agencies switched to a more conservative rating mechanism.

Next, we control for the risk of CMBS deals and examine whether evidence exists for the shift of equilibrium before and after the crisis. Specifically, we construct both ex-ante and ex-post measures for the risk. While holding risk fixed, we investigate the AAA subordination level for each CMBS before and after the crisis.

We use the two most important original deal level risk-related characteristics, loan-to-value ratio (LTV) and debt-service coverage ratio (DSCR), as ex-ante risk measures. Then, we examine their relationship with the AAA subordination level before and after the crisis. Figures 16 and 17 demonstrate the non-parametric estimation for the mean of the AAA subordination level given LTV and DSCR, respectively. Note that deals issued after crisis on average have lower LTV and higher DSCR, which suggests that, roughly speaking, deals after crisis are safer than pre-crisis deals. In both Figures 16 and 17, however, the mean estimates of the AAA subordination level given LTV and DSCR after the crisis are always significantly higher than those before the crisis. Therefore, safer CMBS deals after the crisis receive smaller proportions of the AAA ratings than deals before crisis.

Higher macroeconomic risk might be associated with the mortgage assets after the crisis, which could also affect the credit rating in a negative way. To control for such effects, we also use the delinquency rate as the ex-post risk measure and examine how it is related to the AAA subordination level before and after the crisis. In particular, we focus on the third year (after its issuance) delinquency rate of a deal. The delinquency rate is defined as the sum of delinquency for at least 90 days, foreclosure, and real estate owned (REO). Intuitively, the delinquency rate summarizes all the ex-post risk information associated with a deal. The Bloomberg data allows us to observe the monthly updated delinquency rates for each deal after its issuance. Alternatively, one can also use the fifth year delinquency rate or a measure with a longer duration. The results are quite similar.

Figure 18 presents the scatter plot for the AAA subordination level and delinquency rate for each deal issued before and after crisis in our sample. For deals issued after crisis (blue dots), the support of the third year delinquency rate is close to degenerate, that is, most deals after 2008 have zero delinquency. Hence, these assets are quite safe. However, the average AAA subordination level is 29.0%, which is significantly higher than 16.3% of assets before the crisis. However, the latter are associated with higher third year delinquency rates. Importantly, the correlation between the AAA subordination level and the delinquency rate is low, which is consistent with the findings in **?**.

Given the empirical evidence discussed above, the CMBS deals issued after the crisis are generally less risky but, on average, granted with lower ratings. As a risk measurement, clearly the AAA subordination level shifts from an inflated to a conservative rating equilibrium.

2.4 Estimation Procedure

As emphasized above, the peer effects coefficient α can be identified if and only if the equilibrium shifts from one to another in the data. We now discuss how to estimate α from an iid pooled cross-sectional random sample $\{(p_i, x_i, t_i) : i = 1, \cdots, n\}$. To obtain a precise estimator, we further impose a parametric specification on the nonstrategic part $\beta(\cdot)$ as an approximation, which allows us to estimate α at the regular $\sqrt{n}$-rate. Specifically, let $\beta(x) = x'\beta_0$ for some $\beta_0 \in \mathbb{R}^d$. We further denote $\theta_0 = (\alpha_0, \beta_0')' \in \Theta \subseteq \mathbb{R}^{d+1}$, where Θ is a compact parameter space. Hence, our econometric model becomes:

$$\Phi^{-1}(p) = x'\beta_0 + \alpha_0 p^e(x,t) + \epsilon. \tag{2.7}$$

where $p^e(x,t) = \mathbb{E}(p|x,t)$.

We now proceed to motivate and describe our estimation procedure. Note that (2.7) is a typical transformed regression equation, albeit that we do not observe $p^e(x_i,t_i)$ directly. In the first stage, we nonparametrically estimate it by $\hat{p}^e(x_i,t_i) = \hat{\psi}_i/\hat{\sigma}_i$, where

$$\hat{\sigma}_i = \frac{1}{(n-1)h^d} \sum_{j \neq i} K\left(\frac{x_j - x_i}{h}\right) \cdot \nVdash(t_j = t_i),$$
$$\hat{\psi}_i = \frac{1}{(n-1)h^d} \sum_{j \neq i} p_j \cdot K\left(\frac{x_j - x_i}{h}\right) \cdot \nVdash(t_j = t_i),$$

where $K : \mathbb{R}^d \to \mathbb{R}$ and $h \in \mathbb{R}$ are kernel function and bandwidth, respectively. Note that the above kernel estimator leaves the i-th observation out, which is standard in the kernel estimation literature. **?** state conditions under which the nonparametric estimator $\hat{p}^e(x_i,t_i)$ is consistent and asymptotically normal distributed.[13]

In the second stage, we regress $\Phi^{-1}(p)$ on x and the generated regressor $\hat{p}^e(x,t)$. Similarly to **?**, we introduce a weighting function to avoid the trimming issue introduced by the first stage nonparametric kernel estimation, that

[13] Alternatively, one can use the series expansion approach to estimate $p^e(x_i,t_i)$; see **?**.

is, the denominator $\hat{\sigma}_i$ might be close to zero for some observations with small densities of x. Specifically, using $\hat{\sigma}_i$ as the weighting function, our estimator has a form of the weighted least squares estimator as the following:

$$\hat{\theta} = \left(\sum_{i=1}^{n} \hat{\sigma}_i^2 \hat{w}_i \hat{w}_i'\right)^{-1} \sum_{i=1}^{n} \hat{\sigma}_i^2 \hat{w}_i \Phi^{-1}(p_i), \tag{2.8}$$

where $\hat{w}_i = (\hat{p}^e(x_i, t_i), x_i')'$.

We now establish the consistency and asymptotic normality of the proposed estimator under the homoskedasticity assumption. The difficulty comes from the fact that one regressor $\hat{p}^e(x_i, t_i)$ is obtained from the nonparametric kernel estimate.

Assumption C (homoskedasticity). *Let* $\mathbb{E}(\epsilon^2|x) = \sigma_\epsilon^2 < \infty$.

Theorem 1. *Suppose conditions in Lemma 1 and assumption C hold. Let* $\{(p_i, x_i, t_i) : i = 1, \cdots, n\}$ *be an iid random sample. Moreover, let* $h \to 0$ *and* $\sqrt{n}h^d \to \infty$ *as* $n \to \infty$. *Then* $\hat{\theta} \xrightarrow{p} \theta_0$ *and*

$$\sqrt{n}(\hat{\theta} - \theta_0) \xrightarrow{d} N(0, \Sigma)$$

where Σ *is defined in Appendix 1.2.*

Proof. See Appendix 1.2.

Because the equilibrium beliefs $p^e(x_i, t_i)$ is estimated by $\hat{p}^e(x_i, t_i)$ in the first stage, this will induce some efficiency loss, that is, our estimator $\hat{\theta}$ is less efficient than the infeasible estimator that is obtained by replacing $\hat{p}^e(x_i, t_i)$ with $p^e(x_i, t_i)$ in (2.8).

2.4.1 Implementation in R

We utilize the *np* package[14] in R to perform the estimation in the following steps.

First, I estimate p_t^e by utilizing kernel regression function *npreg*. Two separate kernel regressions are performed for $t = 1, 2$. All deal characteristics showed in Table 9 are included in the regression. Second order Gaussian kernel is applied. Second, I estimate σ_i of by utilizing kernel density estimation function *npudens*. Two separate estimations are performed for $t = 1, 2$. Second order Gaussian kernel is applied. Finally, I estimate Equation (2.7) by an OLS regression. The dependent variable is $\Phi^{-1}(p)$ and the independent variables include $\hat{p}_t^e$ and loan characteristics with $\hat{\sigma}_i$ as the regression weights.

2.5 Results

2.5.1 First Stage

Figure 19 presents the result for kernel estimation at the first stage. Two separate kernel regressions are performed for $t = 0, 1$. This Figure plots the relationship between p and $\hat{p}_t^e$. The dots are concentrated around a 45 degree line and this suggests the non-parametric model has a good fit. The coefficients of determination are 98.5% before financial crisis and 88.7% after financial crisis. It is interesting to note that the standard error for the estimation is low, especially for deals issued before the crisis.

[14] **?**

2.5.2 Second Stage

Table 10 presents the result for the main estimation. Model (1) shows the results for benchmark regression without p_t^e. The signs of the impact of risk characteristics on $\Phi^{-1}(p)$ are as expected with some exceptions. An increase in LTV ratio reduces the proportion of AAA rated tranche. The impact of DSCR is the opposite of what we expect. The possible explanation is that, if a loan is approved with low DSCR (corresponding to low debt paying ability), the lender may have other information regarding the loans which may make him believe that the borrower is able to meet the payment with a low DSCR (**?**). Regarding amortization, if a CMBS deal has a bigger proportion of zero and negative amortization loan, the deal is treated as more risky and has less AAA rated tranche. A deal with higher number of loans enjoys diversification benefits, which leads to higher p. Larger deals tend to have higher p as well.

Model (2) presents the estimation results following equation (2.7). First of all, the coefficient on p_t^e is highly significant and positive. The adjusted R^2 is improved from 61 to 93%. This suggests that the model fits much better than the benchmark regression. Second, most coefficients of the loan characteristics are no longer significant. This suggests that the first stage estimator p_t^e with the post crisis dummy explains almost all the variation in AAA subordination level among deals. Moreover, we provide a robust check by including the delinquency at third year as one of the explanatory variables in Model (3). The results are quite similar to those in Model (2). We further investigate how our results are sensitive to the choice of transformation function $\Phi^{-1}(\cdot)$.

In Models (1'), (2') and (3'), we switch to the logit transformation and the results are qualitatively similar.

2.6 Conclusion

In this chapter, we have modeled an agency's rating choice as an incomplete information game with multiple equilibria. We use an exogenous equilibrium shift to identify peer effects in credit rating behaviors. We then apply our method to data on non-agency CMBS deals issued between January 2000 and May 2014. First, we document evidence of an equilibrium shift before and after the 2008 financial crisis. Specifically, using various ex-ante measures of risk, we find that the post-crisis deals are generally less risky but, on average, granted with lower ratings. This result is robust to ex-post measures of risk. Second, we estimate our model using a two-step procedure. After controlling for a host of deal-level characteristics, the inclusion of the peer effects significantly improve the fitness of our model. Our empirical results provide strong evidence of positive peer effects.

Chapter 3

Impact of the Introduction of Competition in the Credit Rating Market

3.1 Introduction

Credit ratings provide information regarding the default probability to investors and allow investors to quickly make investment decisions on complex structured finance products, which are backed by hundreds or thousands of assets. The regulators also strictly follow the credit rating to set capital reserve requirements for financial institutions such as banks and insurance companies. Many institutional investors such as pension funds and money market funds utilize credit ratings to govern their risk management. These attributions make the credit ratings crucial to the financial market. However, during the 2008 financial crisis, structured finance products—which were initially given AAA or high investment-grade ratings—suffered large scale downgrades and defaults. Credit rating agencies were largely blamed for the mismatch between the high level of credit ratings and poor performance of these securities. As a response to the financial crisis, the Dodd-Frank Act was signed into law. The Act aimed to cure the problem by introducing more competition into the credit rating market. Prior to the crisis, only three rating agencies were certified by the SEC as Nationally Recognized Statistical Rating Organizations

(NRSROs). The number has quickly climbed to ten as of March 2015. Among current NRSROs, five rating agencies are actively engaged in the CMBS credit rating market. Kroll Bond Rating Agency (KBRA), the entrant rating agency, quickly gained market share and surpassed the incumbents.[1] After KBRA rated its first CMBS in 2011, its CMBS rating market share quickly rose to 20% in 2012. It has maintained and grown from that level ever since.

The main research question I intend to answer is how the entrant behaved in terms of the ratings issued after they entered the market. To be more specific, I study how KBRA competed against the incumbent rating agencies, whether the ratings issued by the entrant are more lenient or stringent, and whether the entrant gained market share through more favorable ratings. I first study these securities rated by both the entrant and incumbent rating agencies. More than 13.8% of these securities are granted with higher ratings from the KBRA than another rating agency.

Evidence for rating disagreement alone may not be sufficient to prove KBRA's leniency since the securities they rated could be intrinsically safer than those rated by the incumbents. I further perform two additional analyses using deal level and loan level CMBS data to support the evidence. In the first test, I use AAA subordination level as a measure for the average rating of a CMBS and I show that CMBS rated by the entrant were given with a 2.25%

[1]In this study, Morningstar, the rating agency, was formerly an investor-paid but entered the CMBS rating market after acceptance into NRSROs. The market share of Morningstar is much lower compared to the entrant (KBRA) in the study. Morningstar is ignored in this study due to data availability.

larger portion of AAA ratings compared to CMBS rated by another rating agency. In the second test, I utilize seasoned CMBS loans issued prior to the crisis to develop delinquency prediction models. Across all model variations, commercial loans securitized into deals rated by KBRA are predicted to have about 10% higher likelihood to go delinquent compared to other loans. These two pieces of evidence strongly support the case that KBRA systematically gave its CMBS higher ratings while the underlying loans were substantially more risky.

The results of this study have an important policy implication for regulators. Results show that, under current market situation and the issuer pay model, the introduction of new rating agencies does not necessarily improve rating quality. Increasing competition among rating agencies is likely to lead to more space rating shopping and catering behaviors, and consequently causes rating inflation. It seems that the elimination of rating shopping and catering behaviors, and the alteration of the issuer pay model would likely lead to a significant improvement in rating quality.

The remainder of this chapter is organized as follows. The subsequent section provides institutional background and explains the related empirical and theocratical literature on how competition may affect ratings. Section 3 discusses the data. Section 4 presents the methodology and the results following by a conclusion.

3.2 Background

3.2.1 How does competition affect the credit rating market?

Compared to other segments of the structured finance market, CMBS are the most suitable type of security for studying the impact of competition. First, CMBS are part of the structured products that suffered tremendous losses during the financial crisis.[2] However, unlike RMBS and CDO, the new CMBS issuance quickly recovered close to its pre-crisis level despite the intense scrutiny by the market.[3] The issuance recovery gives both the incumbents and entrant the space to compete, and the prospective growth makes it more attractive for all rating agencies to establish and expand their market shares. Second, the CMBS rating process, compared to RMBS and CDO, is deemed more subjective and less quantitative. Thus, the flexibility in the rating process facilitates credit rating agencies' differentiation of their ratings when facing interactions with other market participants. Third, the structure and risk profile of the underlying assets of the CMBS deals issued before and after the crisis generally have remained the same while RMBS and CDO markets have undergone structural changes that are unobservable to the researcher. This feature of the CMBS market is essential for my analysis, which uses performance information prior to the crisis to measure the risk of CMBS issued after the crisis.

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[2] The average downgrade for CMBS issued from 2005-2008 was ten grades.

[3] According to data from Bloomberg, at the peak (i.e. 2006) before the crisis, the number of CMBS, RMBS, and CDO issued are 139, 1864 and 502, respectively. In 2013, the number of CMBS, RMBS and CDO issued are 124, 120, and 8, respectively. (Re-securitized RMBS are not counted.)

The purpose of the Dodd-Frank Act, the most significant change to financial regulation following the financial crisis, was to promote competition among credit rating agencies by recognizing more agencies with NRSRO status. The Act sought to "improve ratings quality for the protection of investors and in the public interest by fostering accountability, transparency, and competition in the credit rating industry."[4] As of March 2015, ten organizations were designated as NRSORs, compared to merely three prior to the financial crisis.[5] However, the reform did little if anything for the conflict of interest regarding the revenue sources of rating agencies, that is, the issuer-pay model.

The regulatory body has claimed that the introduction of more competition helps to improve rating quality. However, both empirical and theoretical literature hardly support this claim. Empirical evidence mainly supports the idea that competition tends to lower the rating quality. **?** use the acceptance of DBRS to NRSROs as an event and show that SEC recognition leads to a corporate bond yields change in the direction implied by DBRS's rating. The paper also suggests that this acceptance reduces the informativeness of the entry's rating since the ratings issued by DBRS are more similar to the other incumbent agencies after becoming a NRSRO. **?** utilize the recapitalization of Fitch as a material entry of the third player to the two agencies market in corporate bond rating. Their study shows that the increased competition co-

[4]Report of the Senate Committee on Banking, Housing, and Urban Affairs to Accompany S. 3850, Credit Rating Agency Reform Act of 2006, S. Report No. 109-326, 109th Cong., 2d Sess. (September 6, 2006) (Senate Report), p. 1.

[5]http://www.sec.gov/ocr.

incides with lower rating quality from the incumbents, which is demonstrated by the inflation of ratings, lower correlation between ratings and market yield, and the lowered ability of ratings to predict default. In contrast, **?** show S&P's issued more stringent ratings than the incumbents when it entered a particular segment of the corporate bond market in 2000.

On the theoretical side, **?** suggest that more competition can lead to lower rating quality as the increased number of agencies facilitate rating shopping under the current issuer-pay model. **?** develop a repeated game model and show that competition can induce inflated rating unless the entrant rating agency has a higher reputation than the incumbent. Their study suggests the likelihood that the entrant starts off with a low reputation (and market share) and this low reputation incentivizes them to gain market share by inflating the ratings.

3.2.2 Channels for interactions between credit rating agencies and CMBS issuers.

Two main practical channels of interactions between credit rating agencies and security issuers are discussed in the literature; these channels have meaningful implications about how competition potentially changes rating quality. The first scenario is called "rating shopping" (see for example, **???**). In a pure rating shopping situation, the issuers solicit preliminary ratings (also called shadow ratings) from multiple rating agencies and pick the most favorable one(s). However, the rating agencies do not deviate from their rating criteria to generate biased ratings. The second channel is "rating catering," which refers to the situation wherein rating agencies deviate from their pre-set rating criteria and give inflated ratings in order to compete for market share against other rating agencies (see for example, **???**). The key distinction from rating shopping is that, in rating catering, the rating agencies alter their models to generate higher ratings for business concerns.

Implications of the increased competition on rating quality through each of these channels are certainly debatable. Additional rating agencies offer issuers a larger number of rating agencies from which to shop. Consequently, this may lead to inflated rating by rating shopping alone.[6] Moreover, competition may increase the value of the incumbents' reputation and, thus, improve the quality of the rating.

3.2.3 This Chapter

In a contemporaneous and independent study, **?** focus on the same entrant event and they analyze the impact of the entry of new credit rating agencies on rating levels. They document similar evidence of the market share change after the financial crisis as well as the comparison of ratings between the entrants and the incumbents. In comparison, my paper draws a more conclusive result beyond the scope of their research by using two separate deal level and loan level analyses with controls for underlying risk level of the

[6]It is worth noting that Dodd-Frank Act intended to suppress rating shopping behavior by mandating rating agency to report all solicited preliminary ratings. However, the enforcement of the mandate is up for debate.

security. My study shows that the entrant granted higher ratings in spite of the more risky underlying assets.

In sum, the impact of competition on rating quality remains an empirical question. In this chapter, I examine how the entrant in the CMBS market behaves with respect to their ratings and market share changes.

3.3 Data

3.3.1 Rating Scale

All the rating agencies have comparable rating scale within each other. Although ratings may be expressed by slightly different wordings in their rating criteria, they all have same number of different ratings and the ratings are treated by regulators in the same manner. In Table 11, I map the alphabetical ratings from each of the five rating agencies to numerical values. I assign the highest possible rating, AAA, with value 23; the second highest rating AA+ is assigned with 22, and so on. Note that the value 2 corresponds to "default" and value 1 corresponds to "not rated." All initial ratings of CMBS tranches are between AAA and B-. Ratings higher than BBB- (including BBB-) are called investment grades, which are in general treated as safe assets by investors and regulators.

3.3.2 Sample

CMBS data are obtained from Bloomberg Professional. In this chapter, I focus on the U.S. non-agency CMBS deals issued between January 2011 and

May 2014. The initial credit ratings are available for five rating agencies (S&P's, Moody's, Fitch, DBRS, and KBRA). However, for various reasons, 69 out of 246 deals miss deal level risk characteristics. The majority of deals with missing variables are private placement CMBS deals, since the publication of the deal prospectus is not required by the SEC for this particular type of issuance.

Bloomberg has deal level, tranche level, and loan level data coverage for CMBS. In this study, I utilize all three levels of this data. Deal level data mainly cover the aggregated risk related information such as Loan-to-Value (LTV) ratio, Debt-Service coverage ratio (DSCR), original deal balance, weighted average coupon (WAC), amortization term, and number of loans. Tranche level data mainly include initial and surveillance ratings, interest rate, credit support, and other tranche-specific information. Bloomberg also has abundant coverage on loan-specific information. More than 200 fields are available for loan level data and the variables used in this chapter include LTV, DSCR, loan balance, amortization schedule, and other characteristics related to the risk of the loan.

Table 12 shows the summary statistics for deal level and tranche level information for CMBS in our sample. Several notable observations provide some insights into the CMBS rating market. First, the average number of ratings received by a tranche is 2.45. Most issuers obtained two to three ratings from the five rating agencies. Second, Moody's had the highest market share. Third, the average numerical rating is between 19 and 20 and this suggests an average alphabetic rating of A+ and AA-. If I use tranche balance to calculate weighted average rating, even higher average ratings appear since AAA tranches are usually the biggest portion of a deal.

Table 13 presents the summary statistics for loan level data for CMBS in my sample. For loan level analysis performed in this paper, I use loans originated between 2005-2008 to calibrate delinquency predicting model, and I then utilize the calibrated prediction model to forecast the probability of delinquency for the loans originated between 2011-2014. Panel A shows the statistics for the calibration period and Panel B shows the statistics for the testing period. The statistics illustrate that the delinquency rate for loans securitized in the calibration period are significantly higher than those in the testing period. Moreover, loans in the testing period generally have a safer risk profile.

3.4 Methodology and Results

3.4.1 Market Share Change after the Entry

After the financial crisis, the SEC was encouraged by the Dodd-Frank Act to promote competition in the credit rating market and KBRA became NRSRO on February 11, 2008 (?). KBRA rated its first CMBS deal on January 19, 2011 (?). KBRA claims that "KBRA was established in 2010 in an effort to restore trust in credit ratings by creating new standards for assessing risk and by offering accurate and transparent ratings."[7] Prior to the recognition, KBRA acquired LACE Financial, which primarily focused on ratings of financial institutions.

Figure 20 shows the change in CMBS rating market share by these five credit rating agencies. According to data collected from Bloomberg, KRBA only rated four CMBS deals in 2011 but its market share quickly rose to 20% and surpassed all other rating agencies except Moody's. Since then, it has maintained its market share in CMBS. Interestingly, despite the large volume in CMBS rated by KBRA, KBRA only had 13 credit analysts and supervisors in 2011 compared to 1,345 at S&P's and 1,204 at Moody's (**?**).

3.4.2 Rating Comparison between the Entrant and the Incumbents

Each tranche of a CMBS deal is commonly granted more than one rating so rating disagreements are sometimes observed.[8] A new entrant to the credit rating market may give more generous ratings as a potential way to quickly gain market share. Table 14 shows the comparison between ratings issued by KBRA and the incumbents. In Panel A, I document the percentage of "over-rate" which describes the rating agency giving the tranche a higher rating than any of other rating agencies. In 2011, 21.5% ratings issued by KBRA were higher than at least one of the other rating agencies while this rate was only 5% for other agencies. This pattern consistently repeated itself

[7] https://www.krollbondratings.com/overview.

[8] Rating disagreements are more prevalent after the crisis.

in 2012, 2013, and 2014. The "over-rate" percentages were economically and statistically different between KBRA and the rest of the rating agencies.

It appears that KBRA gave more generous ratings than other rating agencies since the inception of its CMBS business. Moreover, this leniency in rating coincides with the surge in its market share against the established incumbents. However, the evidence from rating disagreement alone is not sufficient to make a decisive conclusion for mainly two reasons. First, the deals and tranches rated by KBRA may just be intrinsically less risky. Thus, in this case, KBRA may just issue accurate ratings rather than being generous. Second, the rating disagreement approach ignores the information for these deals that is not rated by KBRA and the approach also does not incorporate the CMBS risk-related information of the CMBS. In the following two sections, I provide further evidence that KBRA gives more lenient ratings than the incumbents after controlling for the risk of CMBS.

3.4.3 AAA Subordination Level Comparison between the Entrant and the Incumbents

In this section, I use a measure of average rating received by a CMBS deal and I show that CMBS rated by KBRA are granted with higher ratings, even after controlling for deal level risk characteristics and time fixed effects. AAA subordination level—the fraction of a CMBS that does not receive AAA ratings—is a common measure for a deal's average rating. AAA subordination level equals the maximum amount of losses a deal may sustain before the loss is allocated to AAA tranches. Thus, a higher level corresponds to a lower rating. Following Equation (3.1), I run a regression with the AAA subordination level as the dependent variable on an indicator variable that equals one if the deal is rated by KBRA. I also control for various risk characteristics and time fixed effects.

$$AAASubordinationLevel_i = \alpha_0 + \beta_1 RatedbyKBRA_i + \gamma Controls_i + YearFEs + \epsilon_i \tag{3.1}$$

Table 15 presents the regression results. Model (1) is the baseline regression that does not include the indicator variable for rating agency. Model (2) shows that being rated by KBRA reduces the AAA subordination level (i.e. higher average deal rating) by 2.25% and the impact is significant at a 95% level.

3.4.4 Predicted Probability of Delinquency Comparison between the Entrant and the Incumbents

In the previous section, I used the AAA subordination level and risk characteristics to show that CMBS rated by KBRA are granted with higher ratings compared to those rated by other agencies. In this section, I further strengthen my analysis by demonstrating that the loans included in the deals rated by KBRA are inherently more risky than other loans.

I follow a three-step procedure for this analysis. In the first step, I use historical performance data for seasoned commercial mortgage to develop prediction models based on the delinquency status, risk characteristics, and location of the property. In the second step, the calibrated prediction models are applied to the newly-issued loans since 2011 to get the predicted probability of delinquency. Finally, I use a regression analysis to study whether those loans included in the CMBS rated by KBRA are more risky than the rest of the loans.

Table 16 shows the regression used to calibrate two types of prediction models. Model (1) uses an OLS regression with delinquency status of the loan as the dependent variable and risk characteristics as explanatory variables. Model (2) adopts a logistic regression instead of an OLS regression. For Models (3) and (4), I use 2000-2008 data instead 2005-2008 data used in Models (1) and (2). Models (1) and (3) follow an OLS regression and Models (2) and (4) follow logistic regression. Nevertheless, these models produce similar results in terms of predicted probability of delinquency. It is worthwhile to note that the directions of the coefficients presented in the models align with my expectation.

After calibrating the model and producing predicted delinquency probability for loans securitized between 2011-2014, following Equation (3.2), I run a regression with the predicted delinquent probability as a dependent variable and the indicator variable, which equals one when the loan is included into a CMBS deal rated by KBRA. Table 17 shows that those loans securitized into KBRA CMBS are on average more likely to be delinquent for 0.5% - 1.6%. The magnitudes are significant at a 99% level. This relative difference from the average predicted probability (ranging from 6.9%-13.3%) of delinquency is very substantial (about 10% more likelihood).

$$PredProbofDelq_i = \alpha_0 + \beta_1 RatedbyKBRA_i + QuarterFEs + \epsilon_i \qquad (3.2)$$

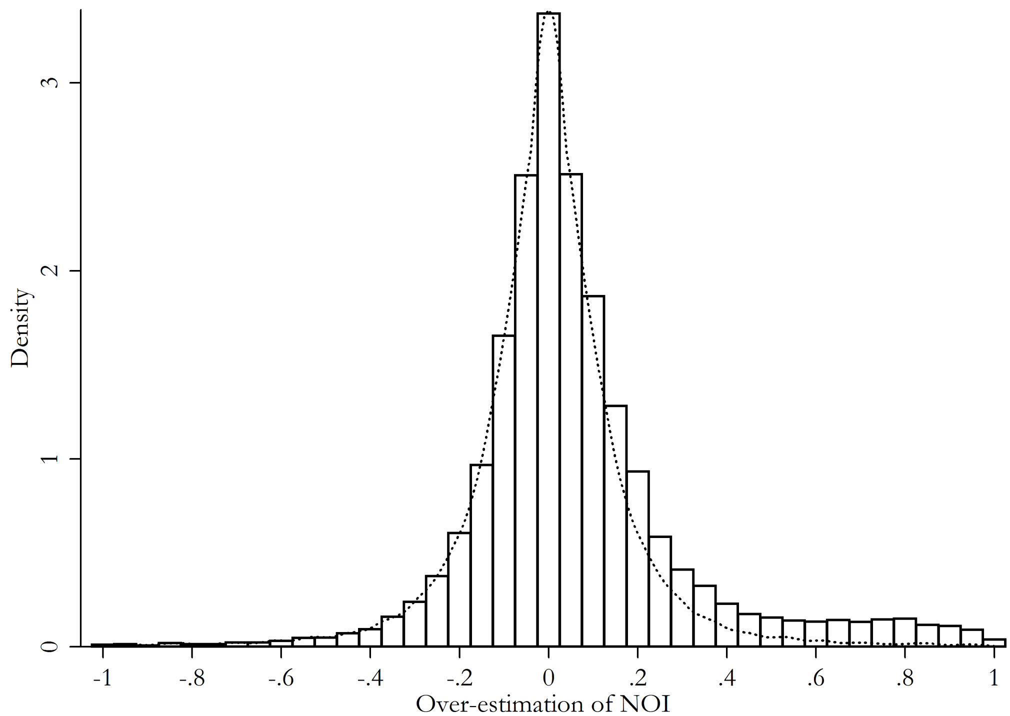
3.5 Conclusion

In this chapter, I have examined the entry of KBRA into the CMBS market. The entrant gives more generous ratings on the same securities, which also received ratings from the incumbents. From 2011-2014, 13.8% of the CMBS tranches rated by KBRA were granted higher ratings compared to the 7.3% for other rating agencies. The leniency in ratings coincides with the quick market share surge by KBRA. In the second year after KBRA entered the CMBS market, its market share had already risen up to 20%, and it has maintained and grown its share ever since. I further performed two additional analyses to test whether KBRA gave more generous ratings after controlling risk characteristics of CMBS. A deal level analysis shows that deals rated by KBRA have a 2.25% less AAA subordination level than other deals. This difference translates to a substantial benefit to the bond issuer since the increase in the AAA-rated portion of CMBS leads to less interest payment to bond investors due to its AAA rating. In a loan level analysis, I used historical realized delinquency to predict the delinquent probability of newly issued CMBS loans. The evidence shows that loans securitized into deals rated by KBRA, on average, have about a 10% higher likelihood of becoming delinquent. All of this evidence confirms that KBRA was more lenient on CMBS ratings and its deal was more risky than the incumbents'.

The policy implication of this chapter is straightforward: regulators should rethink their strategy of promoting more competition to improve rating quality. Since CMBS rated after entry have a limited life and business cycle exposure, it is still too early to judge the accuracy of the ratings based on realized performance. The nature of the real estate market suggests that a multi-decade time horizon is needed to judge the performance of the rating models and criteria. As time goes by, it will interesting to study how the incumbent rating agencies react to the rating leniency by the entrant.

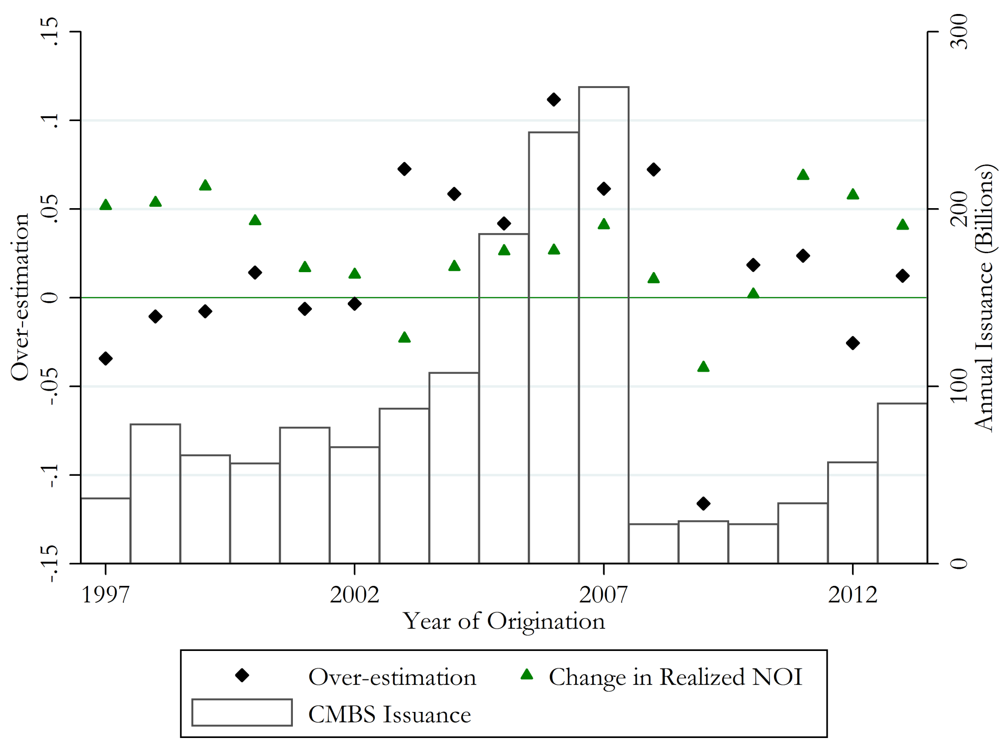
Figures

Figure 1: Histogram of Over-estimation.



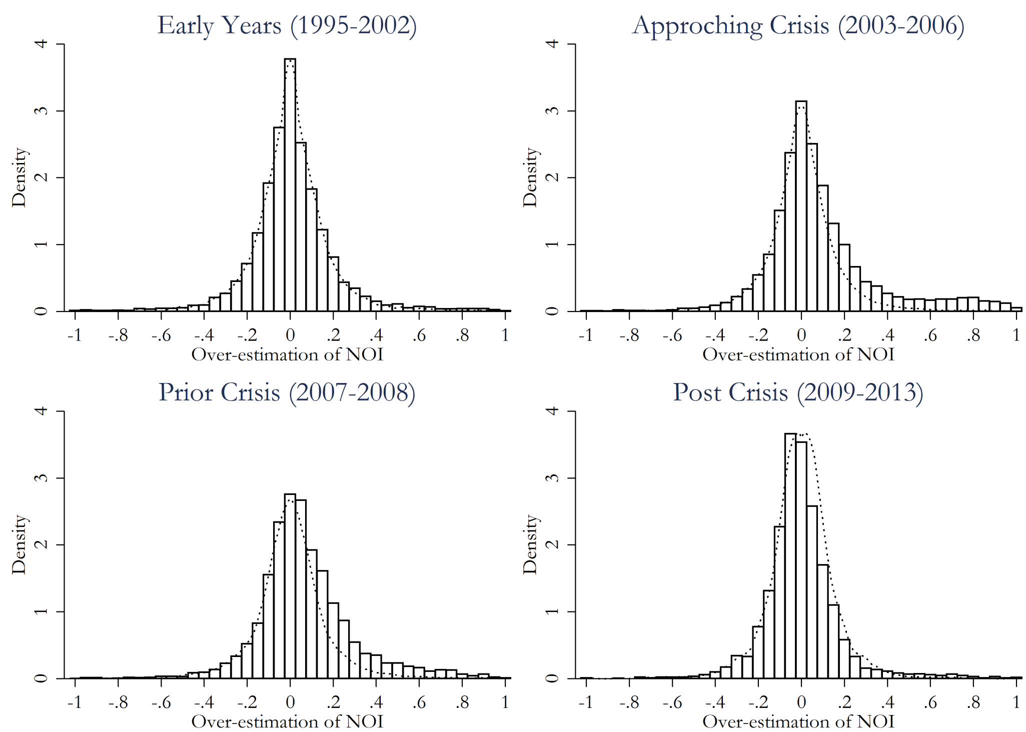
This figure presents the histogram of over-estimation of NOI for years between 1995 and 2006. Over-estimation of NOI is calculated by comparing UW NOI and Realized NOI of origination year following Equation 1.3. The dotted line is drawn by symmetrically mirroring the kernel density estimation for negative values at zero.

Figure 2: Average Over-estimation by Year of Origination.



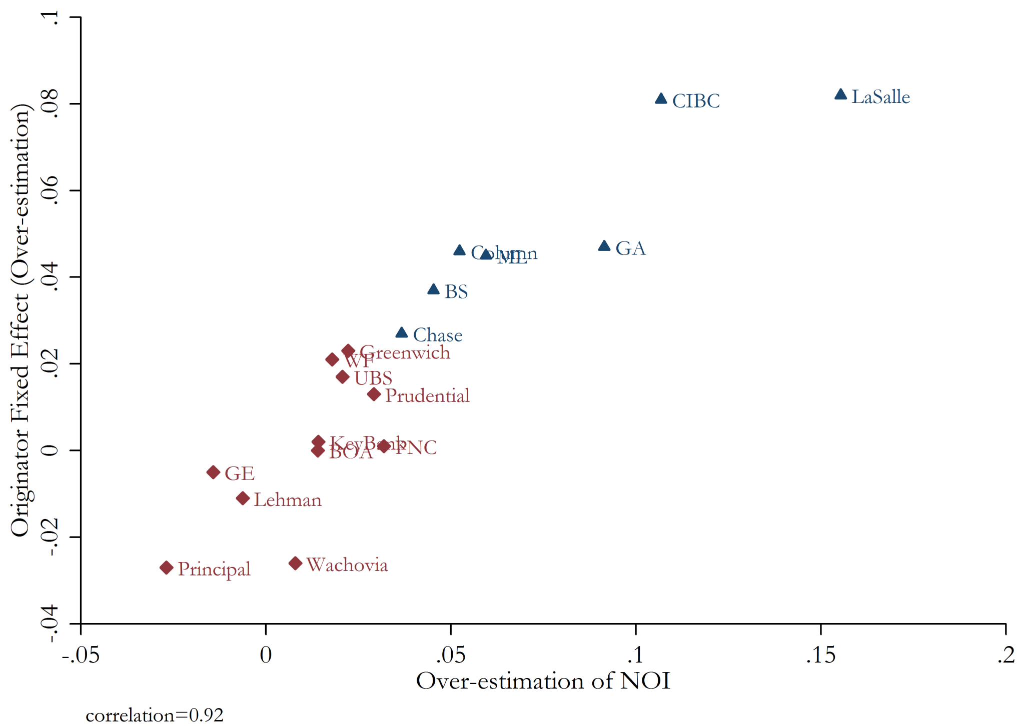
This figure presents the average over-estimation of NOI by loan origination year. The data range from 1997 to 2013. The 1995 and 1996 over-estimation are not plotted due to limited sample size. Annual issuance for U.S. non-agency CMBS is presented on the right y axis.

Figure 3: Comparison of Over-estimation in Different Periods.



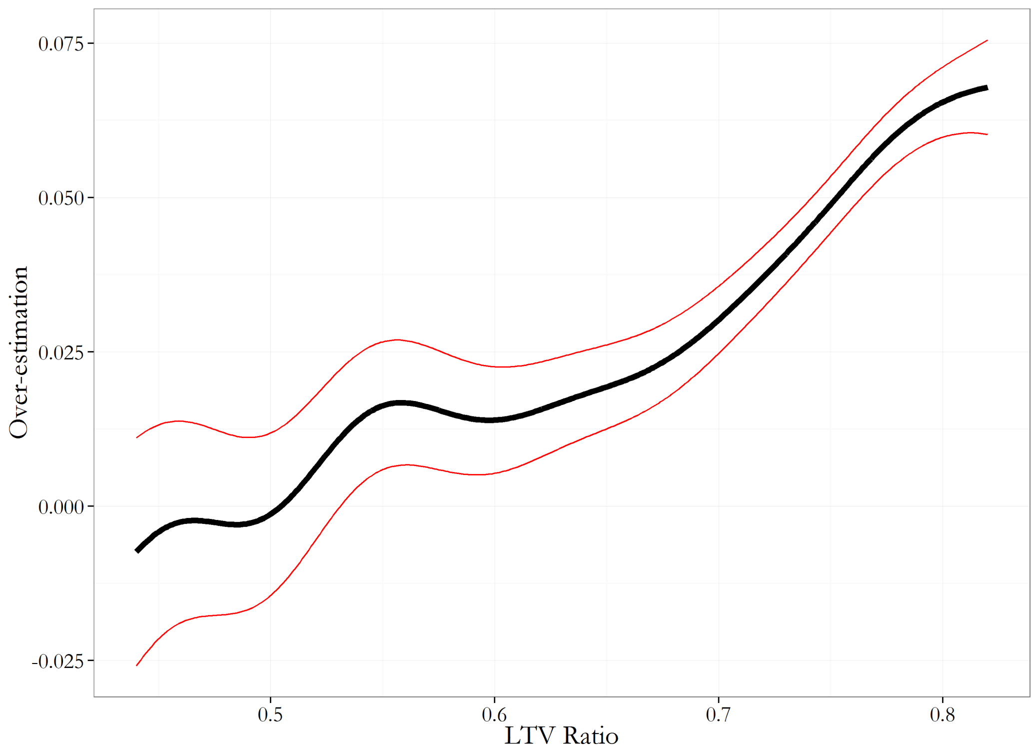
This figure compares the histogram of over-estimation of NOI in different time periods. Over-estimation of NOI is calculated by comparing UW NOI and Realized NOI of origination year following Equation 1.3. The dotted line is drawn by symmetrically mirroring the kernel density estimation for negative values at zero.

Figure 4: Over-estimation and Originator Fixed Effect.



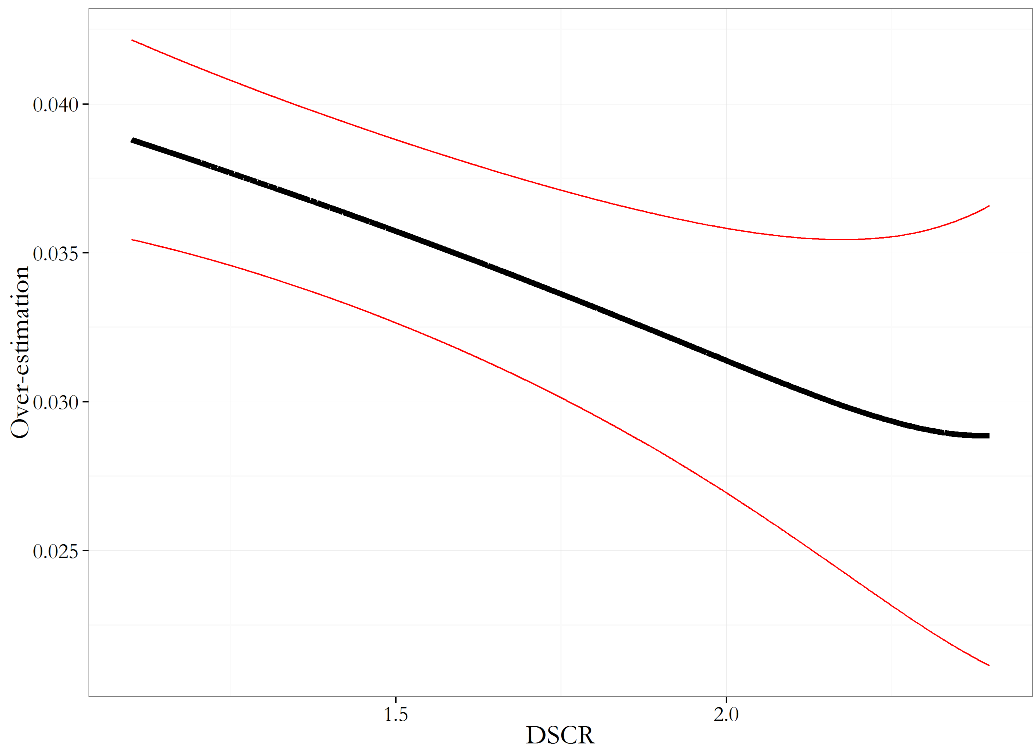
The figure presents the scatter plot between average over-estimation aggregated by originator and originator fixed effect on over-estimation. Originators with at least 500 available samples from 1995 to 2006 are included. The originator fixed effects are from an OLS regression of over-estimation of NOI on loan characteristics with state fixed effects and quarter of origination fixed effects. Standard errors are sandwich estimators. The triangle markers indicate that the fixed effects are significant at a 5% level. Bank of America is the reference originator.

Figure 5: Kernel Regression of Over-estimation and LTV Ratio.



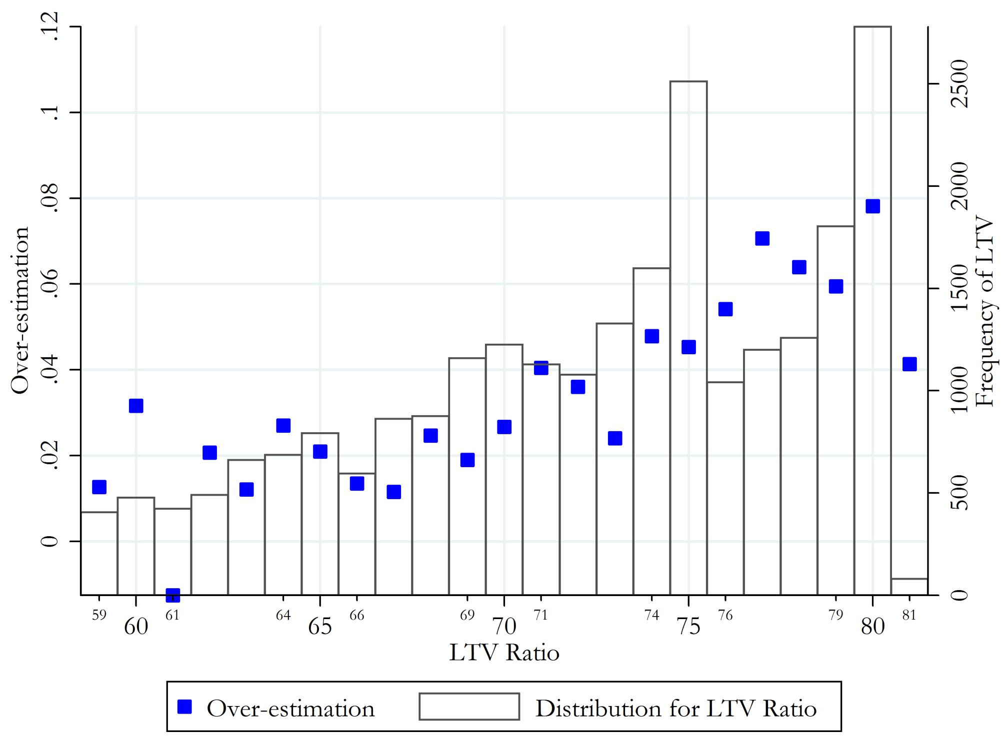
This figure shows the kernel regression of over-estimation on LTV ratio. The kernel regression uses second order Gaussian kernel with fixed bandwidths. The red lines are at a 95% confidence interval.

Figure 6: Kernel Regression of Over-estimation and DSCR.



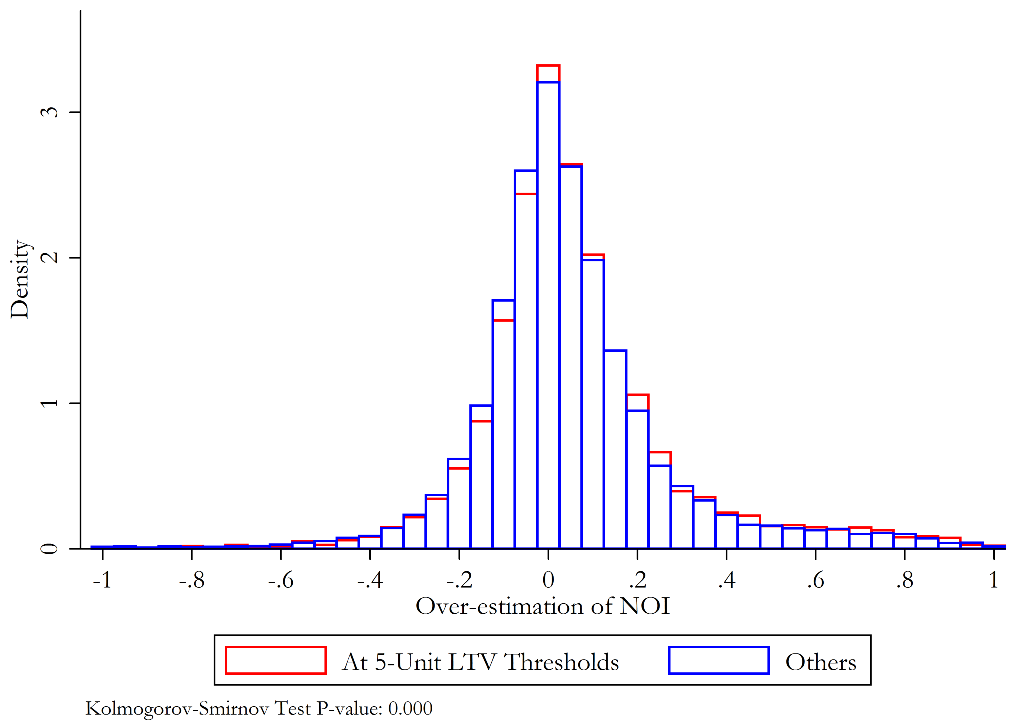
This figure presents the kernel regression of over-estimation on DSCR. The kernel regression uses second order Gaussian kernel with fixed bandwidths. The red lines are at a 95% confidence interval.

Figure 7: The Relationship between Over-estimation of NOI and LTV.



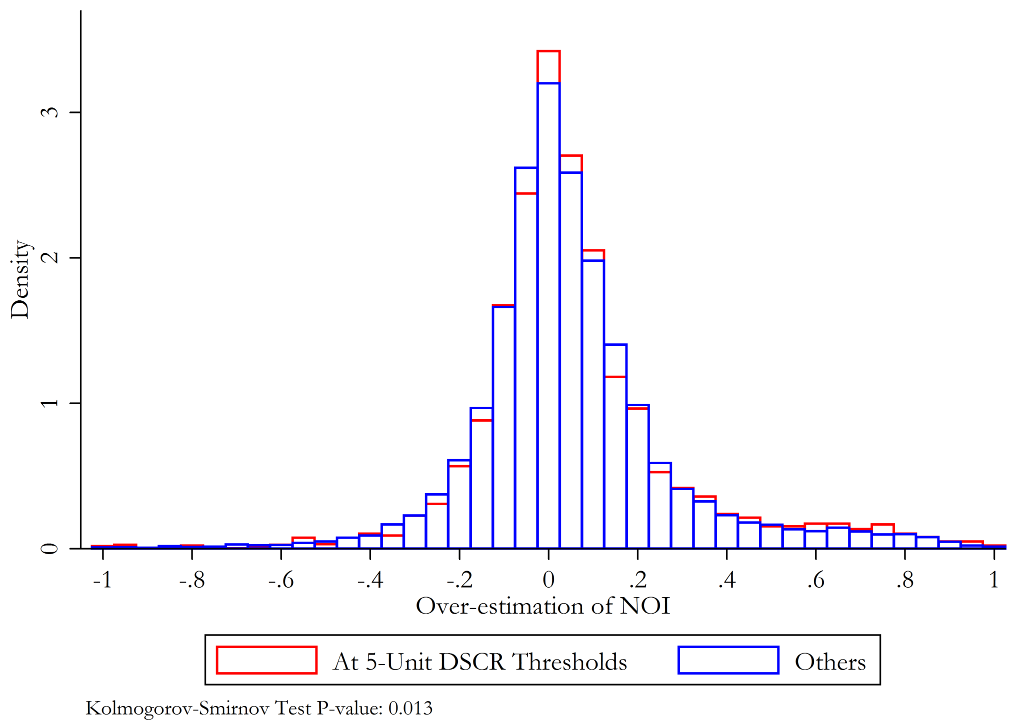
This figure presents the relationship between Over-estimation of NOI and LTV. Over-estimation of NOI is calculated by comparing UW NOI and Realized NOI of origination year following Equation 1.3. This histogram of initial LTV ratio is plotted.

Figure 8: Histogram of Over-estimation for LTV on and off 5-unit Thresholds.



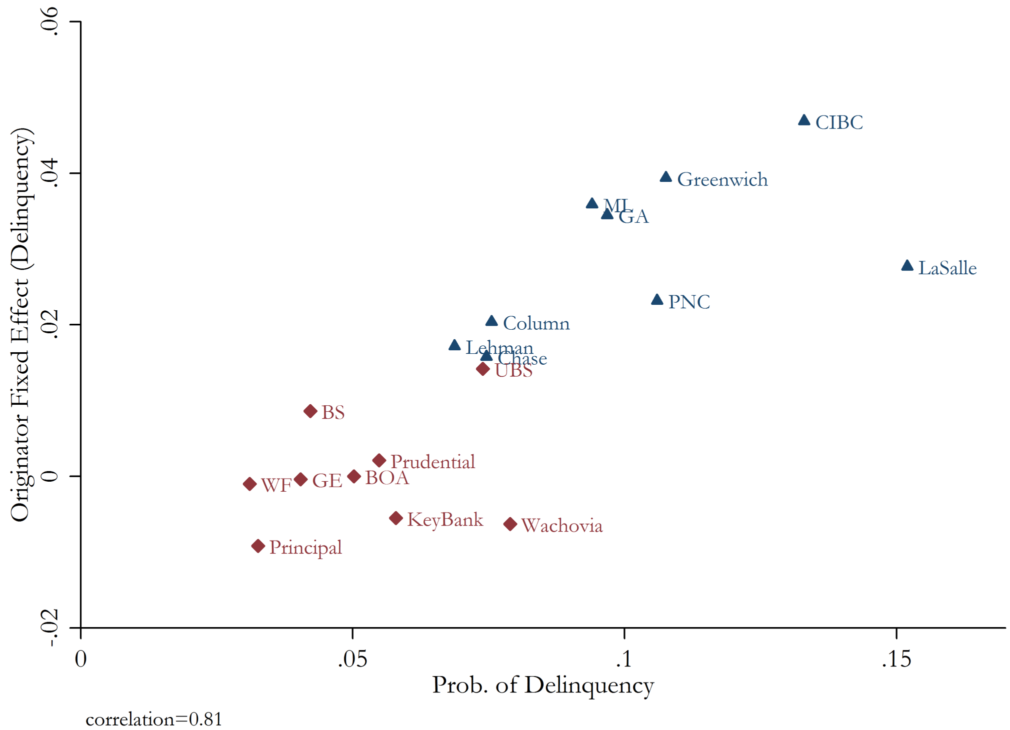
This figure presents the histogram for loans with LTV at 5-unit thresholds (e.g. 75% and 80%) and the other loans. Over-estimation of NOI is calculated by comparing UW NOI and Realized NOI of origination year following Equation 1.3. Loans with over-estimation between -100% and 100% are included. The Kolmogorov-Smirnov test is used to the test the equality of the distributions.

Figure 9: Histogram of Over-estimation for DSCR on and off 5-unit Thresholds.



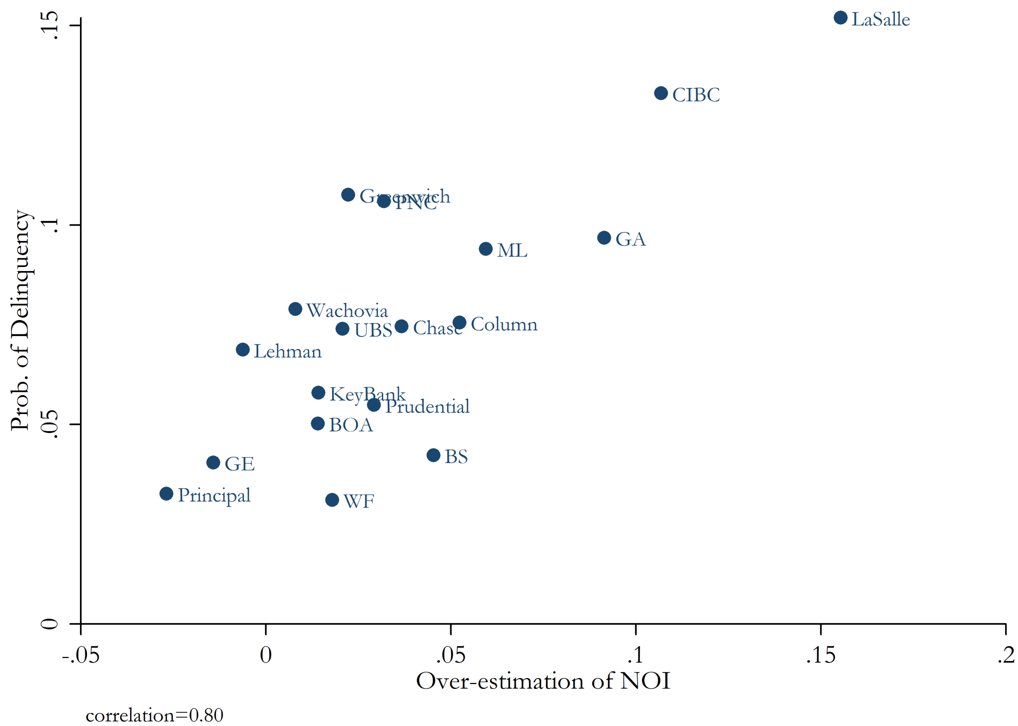
This figure presents the histogram for loans with DSCR at 5-unit thresholds (e.g., 1.20 and 1.25) and the other loans. Over-estimation of NOI is calculated by comparing UW NOI and Realized NOI of origination year following Equation 1.3. Loans with over-estimation between -100% and 100% are included. The Kolmogorov-Smirnov test is used to the test the equality of the distributions.

Figure 10: Probability of Delinquency and Originator Fixed Effect.



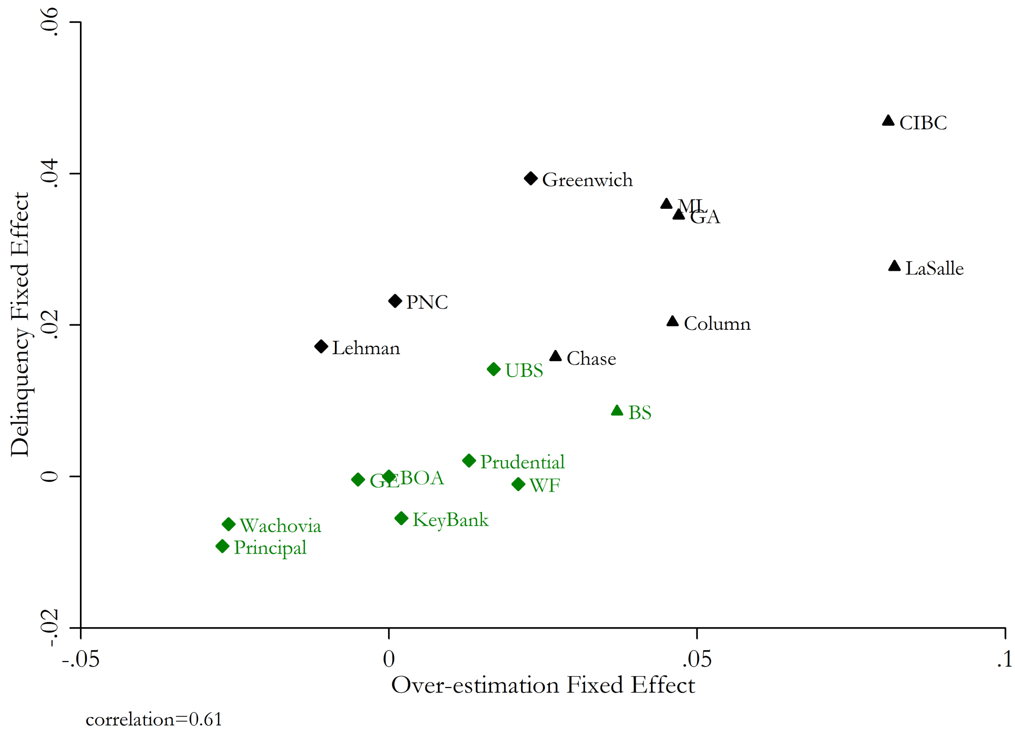
The figure presents the scatter plot between average delinquency aggregated by originator and originator fixed effect on delinquency. Originators with at least 500 available samples from 1995 to 2006 are included. The originator fixed effects are the results from OLS regression of delinquency status dummy on loan characteristics with state fixed effects and a quarter of origination fixed effects. Standard errors are sandwich estimators. The triangle markers indicate the fixed effects are significant at a 5% level. Bank of America is the reference originator.

Figure 11: Over-estimation and Probability of Delinquency by originators.



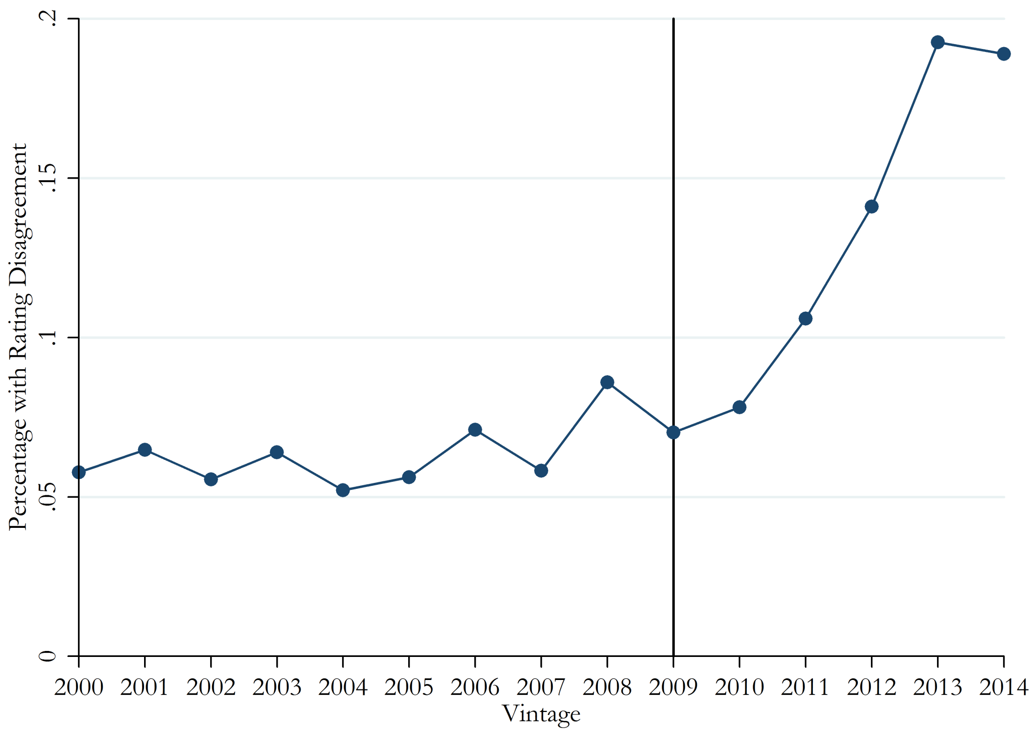
The figure presents the scatter plot between average over-estimation and average delinquency aggregated by originator. Originators with at least 500 available samples from 1995 to 2006 are included.

Figure 12: Originator Fixed Effects for Over-estimation and Delinquency.



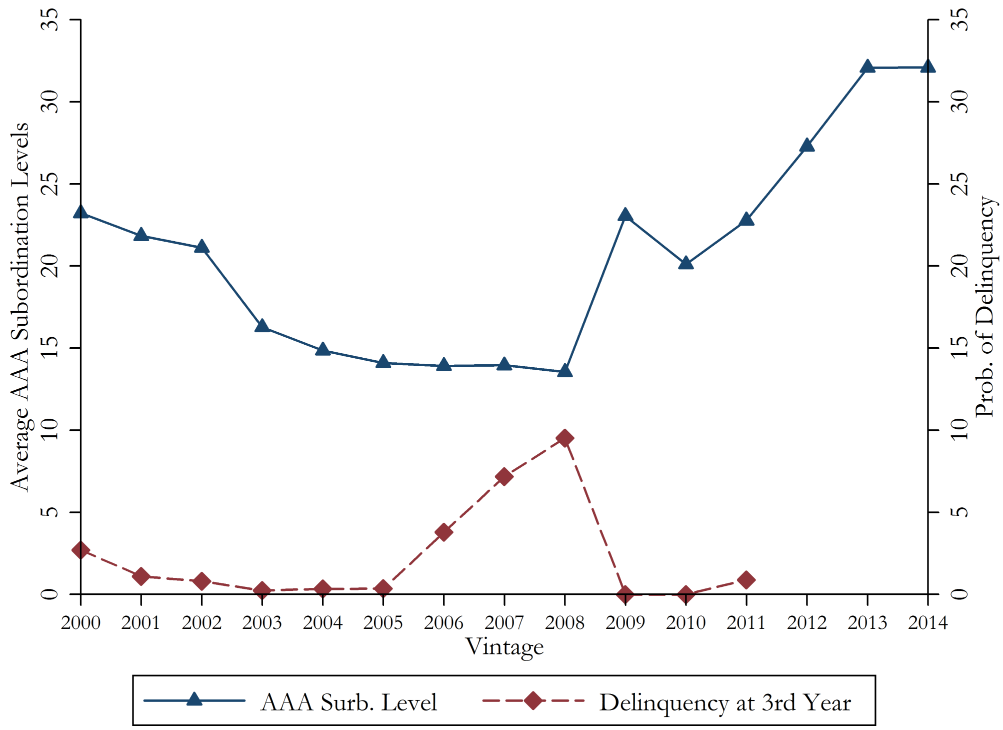
The figure presents the scatter plot between originator fixed effects on over-estimation and delinquency. Originators with at least 500 available samples from 1995 to 2006 are included. The originator fixed effects are the results from OLS regression of over-estimation and delinquency status dummy, respectively, on loan characteristics with state fixed effects and quarter of origination fixed effects. Standard errors are sandwich estimators. The triangle markers indicate that the over-estimation fixed effects are significant at 5% level. The black markers indicate that the delinquency fixed effects are significant at 5% level. Bank of America is the reference originator in both regressions.

Figure 13: Percentage of Rating Disagreements by Vintage.



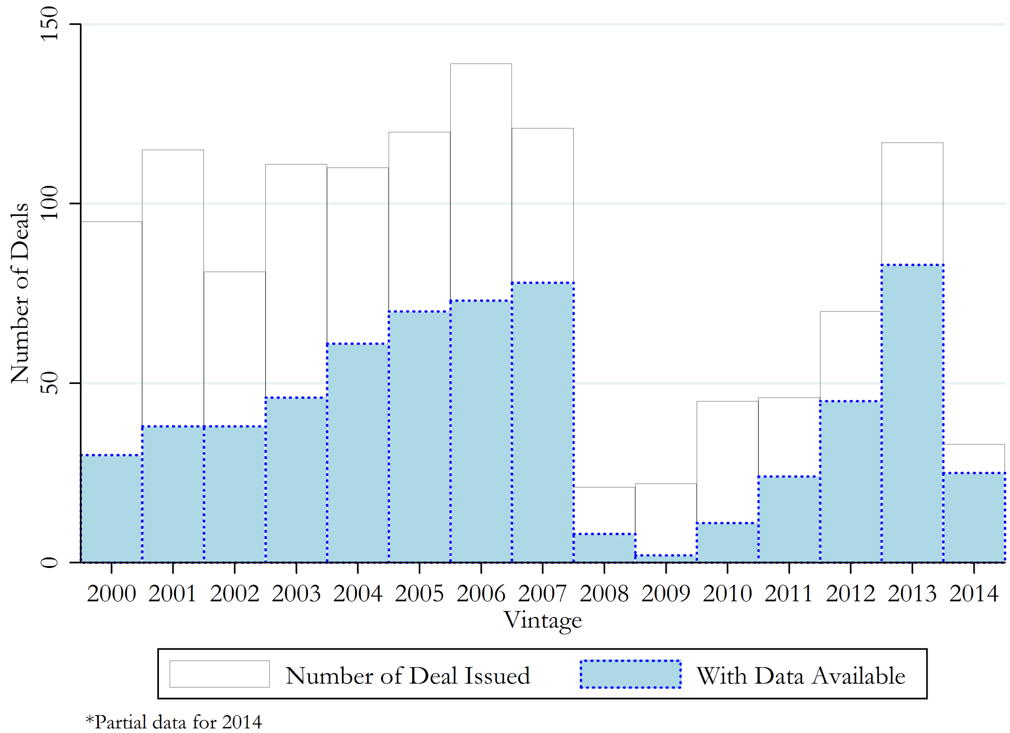
This figure presents percentage of CMBS tranches with rating disagreement by vintage. We define initial rating as the credit rating received within 90 days after the settlement date. We restrict the sample to ratings provided by Nationally Recognized Statistical Rating Organizations.

Figure 14: Comparison of AAA Subordination Level and Delinquency.



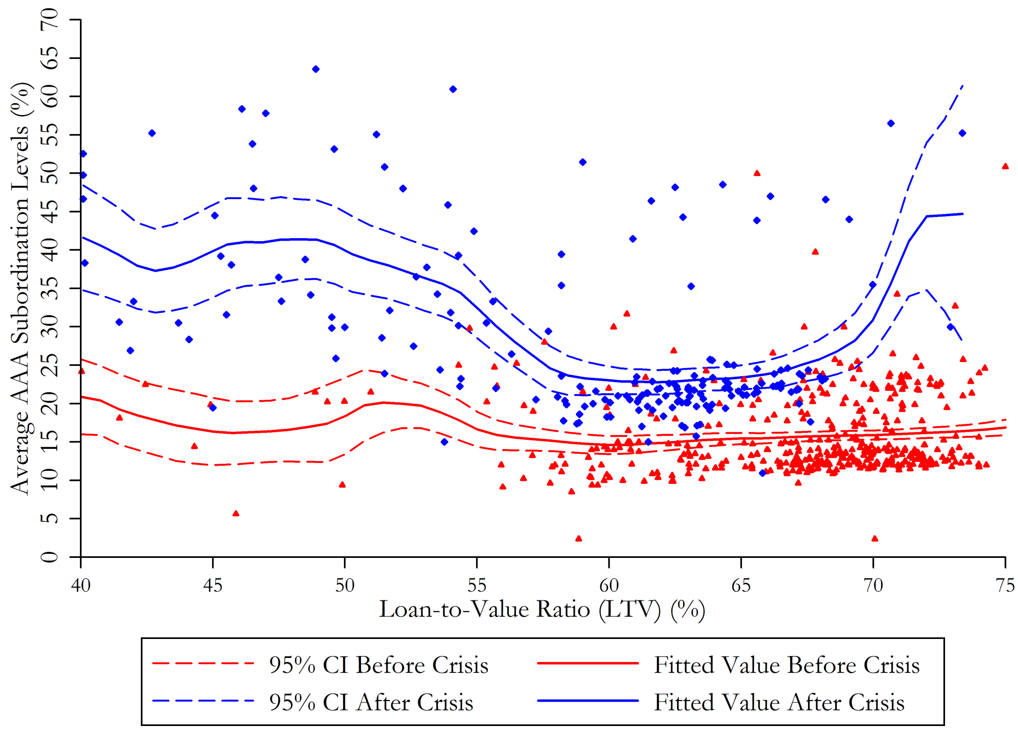
This figure presents the average AAA subordination level and Severe Delinquency of CMBS in the sample by the year of issuance. The subordination level is the sum of the balance of non-AAA tranche divided by the total balance of the deal. The Severe Delinquency is the proportion of the underlying loans which are delinquent for 90 days or longer. The severe delinquency values are captured at the third year origination date of CMBS deals. Both values are presented in percentages.

Figure 15: Annual CMBS Issuance by Year.



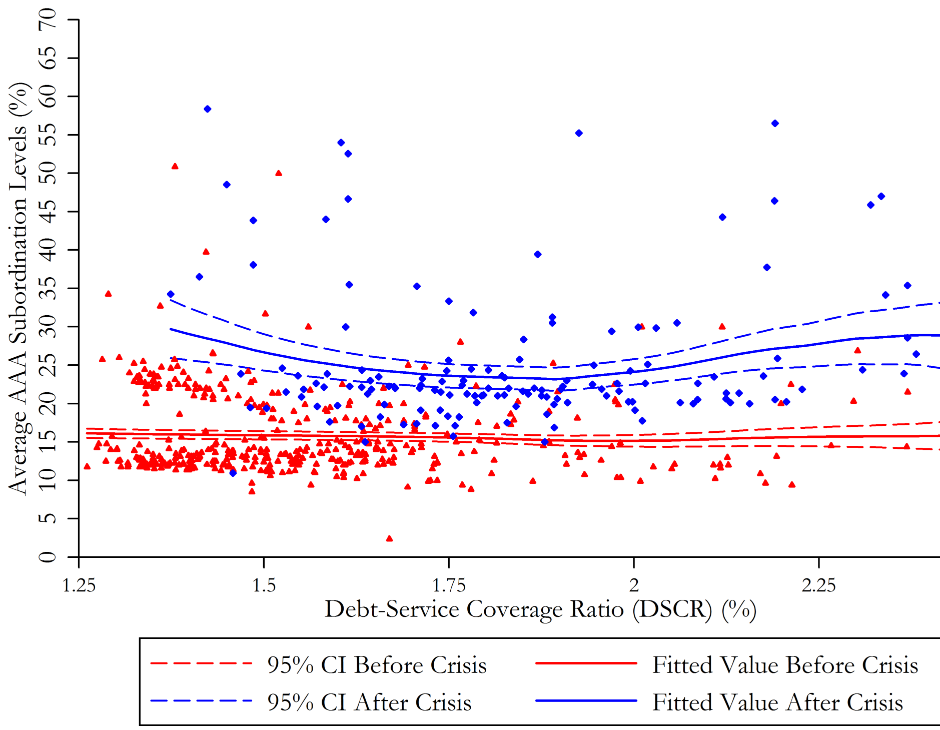
This figure presents the number of CMBS issued by vintage. Our statistics only contain non-agency CMBS. The data are collected from Bloomberg.

Figure 16: AAA Subordination Level and LTV.



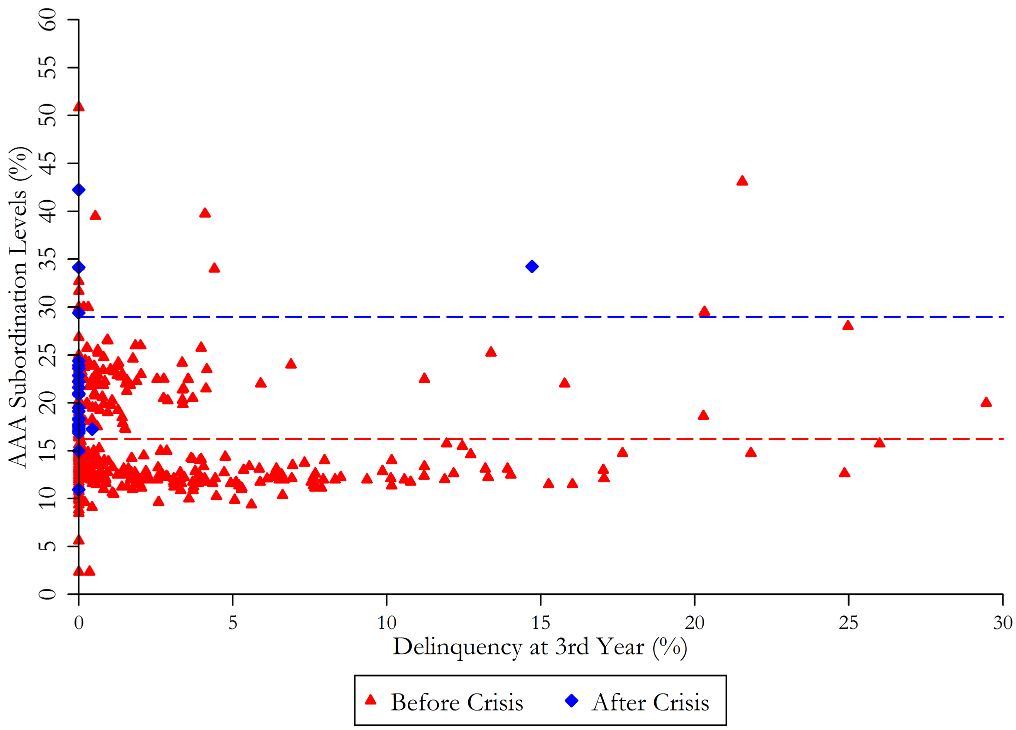
This figure presents the scatter plot of AAA subordination levels and loan-to-value ratios. The subordination level is the sum of the balance of non-AAA tranche divided by the total balance of the deal. Samples outside the range of the figure are ignored. AAA subordination level and LTV are presented in percentages.

Figure 17: AAA Subordination Level and DSCR.



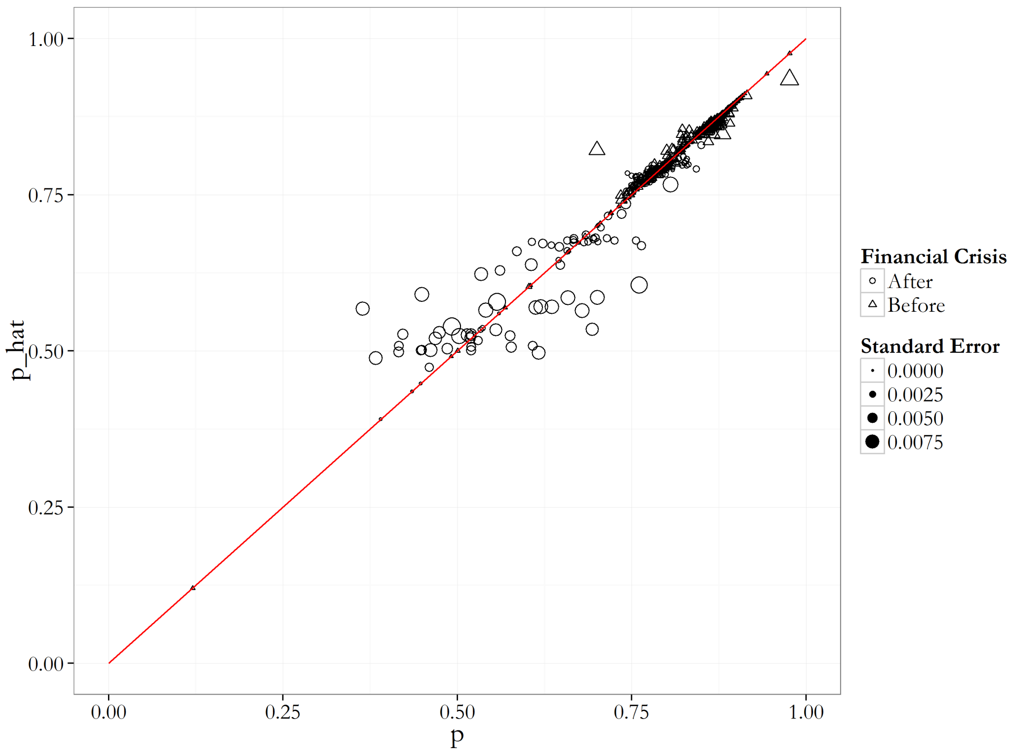
This figure presents the scatter plot of AAA subordination level and debt-service Coverage Ratio (DSCR). The subordination level is the sum of the balance of non-AAA tranche divided by the total balance of the deal. Samples outside the range of the figure are ignored. AAA subordination level are presented in percentages.

Figure 18: AAA Subordination Level and Delinquency at Third Year.



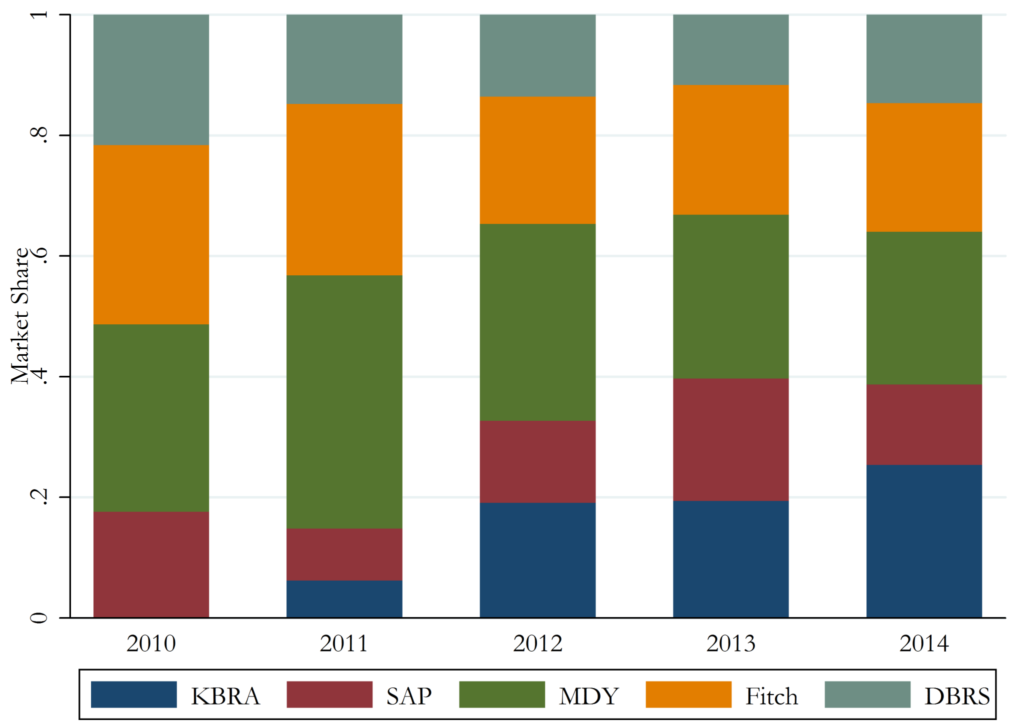
This figure presents the scatter plot of AAA subordination level and Severe Delinquency at the end of the third year after origination. The subordination level is the sum of the balance of non-AAA tranche divided by the total balance of the deal. The Severe Delinquency is the proportion of the underlying loans which are delinquent for 90 days or longer. The severe delinquency values are captured at the third year after origination date of CMBS deals. Two dashed lines mark the average AAA subordination level before and after the crisis, respectively. 96.6% of pre-crisis CMBS have lower AAA subordination levels than the average level of post-crisis CMBS. Both values are presented in percentages.

Figure 19: Non-parametric Estimation on Proportion of AAA Rated Tranche.



This figure presents the scatter plot of the proportion of AAA rated tranche (p) and its predicted value ($\hat{p}_t^e$). The proportion of AAA rated tranche is the sum of the balance of all AAA rated tranche divided by the total balance of the deal. The size of the marker shows the standard error for the kernel estimation. Round markers correspond to deals before financial crisis ($\leq$ 2008) while triangle makers refer to post financial crisis ($\geq$2009). The red line is the 45° line.

Figure 20: Change in Rating Agencies' Market Share.



This figure presents the change in market share over time. Market shares are calculated at a deal level. Total market share is normalized to 1.

Tables

Table 1: Summary Statistics for Delinquency and Loan Characteristics.

Variable	N	Mean	SD
Delinquency	96816	0.07	0.25
LTV	92906	0.67	0.13
DSCR	91121	1.61	1.55
Original Balance (Million)	96816	10.5	58.0
Coupon	96815	7.09	1.51
Term	96816	152.05	79.77
Fixed	96816	0.93	0.26
Multiple Property	96184	0.03	0.18
Partial Amortization	96816	0.42	0.49
Full Amortization	96816	0.50	0.50
Retail	96184	0.32	0.47
Lodging	96184	0.08	0.27
Industrial	96184	0.19	0.39
Multifamily	96184	0.27	0.44

This table presents summary statistics for delinquency status and loan characteristics for CMBS with available loan level data from 1995 to 2013.

Table 2: Over-estimation of NOI by Year of Origination

Year	N	Mean	SD	5 Perc.	25 Perc.	Median	75 Perc.	95 Perc.
1997	657	-0.03	0.34	-0.45	-0.12	-0.01	0.10	0.40
1998	2295	-0.01	0.22	-0.32	-0.10	0.00	0.09	0.30
1999	1354	-0.01	0.26	-0.28	-0.08	0.00	0.07	0.31
2000	1626	0.01	0.26	-0.24	-0.06	0.00	0.10	0.32
2001	2443	-0.01	0.29	-0.28	-0.08	0.00	0.09	0.34
2002	2146	0.00	0.32	-0.30	-0.08	0.00	0.10	0.39
2003	3305	0.07	0.30	-0.24	-0.06	0.03	0.14	0.78
2004	3771	0.06	0.33	-0.28	-0.06	0.03	0.15	0.71
2005	4606	0.04	0.29	-0.25	-0.06	0.02	0.13	0.48
2006	7672	0.11	0.32	-0.25	-0.04	0.05	0.21	0.74
2007	8016	0.06	0.28	-0.26	-0.05	0.04	0.16	0.52
2008	97	0.07	0.19	-0.19	-0.02	0.05	0.15	0.48
2009	38	-0.12	0.60	-2.37	-0.16	0.03	0.10	0.33
2010	274	0.02	0.25	-0.27	-0.08	-0.02	0.08	0.59
2011	1032	0.02	0.29	-0.23	-0.09	-0.01	0.06	0.32
2012	1526	-0.03	0.23	-0.28	-0.09	-0.02	0.06	0.24
2013	486	0.01	0.19	-0.23	-0.07	0.00	0.08	0.27
All	29915	0.05	0.30	-0.27	-0.06	0.02	0.14	0.61

This table presents the average Over-estimation of NOI aggregated by year of origination from 1997 to 2013. 1995 and 1996 statistics are not presented here due to limited sample size. Over-estimation of NOI is calculated by comparing UW NOI and Realized NOI of origination year following Equation 1.3.

Table 3: Over-estimation of NOI by Originators

Originator	N	Mean	SD	5 Percentile	25 Percentile	Median	75 Percentile	95 Percentile
LaSalle	1881	0.16	0.35	-0.26	-0.03	0.09	0.34	0.78
CIBC	768	0.11	0.37	-0.30	-0.04	0.08	0.24	0.75
German American	561	0.09	0.30	-0.21	-0.05	0.04	0.18	0.71
Small Originators	9227	0.07	0.32	-0.26	-0.06	0.01	0.14	0.76
Merrill Lynch	749	0.06	0.30	-0.28	-0.07	0.03	0.15	0.74
Column Financial	2851	0.05	0.29	-0.23	-0.05	0.04	0.15	0.44
Bear Stearns	1223	0.05	0.30	-0.24	-0.05	0.03	0.14	0.50
JPMorgan Chase	1890	0.04	0.32	-0.31	-0.08	0.03	0.15	0.56
PNC	864	0.03	0.24	-0.24	-0.05	0.03	0.12	0.38
Prudential	560	0.03	0.34	-0.36	-0.09	0.02	0.15	0.65
Greenwich	576	0.02	0.25	-0.29	-0.06	0.02	0.12	0.36
UBS AG	683	0.02	0.24	-0.27	-0.06	0.02	0.11	0.31
Wells Fargo	1863	0.02	0.25	-0.25	-0.08	-0.01	0.08	0.50
KeyBank	641	0.01	0.25	-0.29	-0.08	0.00	0.11	0.36
Bank of America	788	0.01	0.34	-0.31	-0.09	0.00	0.10	0.66
Wachovia	976	0.01	0.30	-0.29	-0.05	0.02	0.12	0.33
Lehman Brothers	921	-0.01	0.23	-0.30	-0.09	0.01	0.08	0.30
General Electric	1585	-0.01	0.20	-0.25	-0.08	0.00	0.07	0.23
Principal Commercial Funding	588	-0.03	0.16	-0.20	-0.08	-0.03	0.03	0.18
All	29195	0.05	0.30	-0.26	-0.06	0.02	0.14	0.62

This table presents the average Over-estimation of NOI aggregated by originators. Originators with at least 500 available samples from 1995 to 2006 are included. Over-estimation of NOI is calculated by comparing UW NOI and Realized NOI of origination year following Equation 1.3.

Table 4: Over-estimation of NOI and Loan Characteristics

Over-estimation	(1) Model	(2) Model	(3) Model
LTV	0.12***		0.30***
	(6.21)		(11.28)
DSCR		0.03***	0.09***
		(4.64)	(10.59)
Log Loan Balance	0.02***	0.02***	0.02***
	(7.80)	(9.77)	(8.22)
Coupon	0.02***	0.03***	0.03***
	(3.79)	(5.48)	(6.25)
Term	0.00*	0.00	0.00**
	(1.81)	(1.52)	(1.96)
Fixed	-0.07***	-0.06***	-0.06***
	(-4.50)	(-4.31)	(-4.03)
Multiple Property	0.02	0.02	0.02
	(1.08)	(1.15)	(1.24)
Partial Amortization	-0.04***	-0.02**	-0.00
	(-4.04)	(-2.41)	(-0.38)
Full Amortization	-0.01*	0.01	0.01
	(-1.71)	(0.60)	(1.32)
Retail	0.01**	0.01***	0.01**
	(2.43)	(2.58)	(2.15)
Lodging	-0.04***	-0.04***	-0.05***
	(-5.01)	(-5.73)	(-6.71)
Industrial	0.01	0.00	0.00
	(0.99)	(0.74)	(0.33)
Multifamily	0.03***	0.04***	0.03***
	(5.55)	(6.43)	(5.61)
Constant	-0.57***	-0.65***	-0.95***
	(-10.08)	(-10.40)	(-14.15)
Observations	28,867	28,867	28,867
State FE	YES	YES	YES
Quarter FE	YES	YES	YES
Adj. R-squared	0.0495	0.0488	0.0543

This table presents the regression of over-estimation of NOI on loan characteristics. Over-estimation of NOI is calculated by comparing UW NOI and Realized NOI of origination year following Equation 1.3. Model (1) excludes DSCR, Model (2) excludes the LTV ratio, and Model (3) includes all variables. All regressions include state fixed effects and quarter of origination fixed effects. Standard errors are sandwich estimators. T-statistics are presented in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 5: Interest Rate and Over-estimation

Coupon/Spread	(1) Model	(2) Model	(3) Model
Over-estimation	0.07***	0.09***	0.03
	(6.57)	(5.01)	(1.55)
LTV	0.40***	-0.00	-0.08
	(10.97)	(-0.00)	(-0.68)
DSCR	-0.02***	-0.28***	-0.22***
	(-4.05)	(-3.65)	(-4.86)
Log Loan Balance	-0.11***	-0.13***	-0.11***
	(-27.83)	(-17.99)	(-17.42)
Term	0.00***	0.00***	0.00***
	(16.54)	(8.96)	(7.37)
Fixed	-0.28***	-0.34***	0.80***
	(-8.23)	(-5.87)	(2.77)
Multiple Property	0.09***	0.06	0.09***
	(4.54)	(1.59)	(2.99)
Partial Amortization	0.31***	0.29***	0.12***
	(21.03)	(6.37)	(4.77)
Full Amortization	0.21***	0.22***	0.04*
	(15.66)	(5.59)	(1.81)
Retail	-0.06***	-0.07***	-0.03***
	(-7.96)	(-5.97)	(-2.85)
Lodging	0.07***	0.13***	0.06***
	(6.28)	(5.64)	(3.43)
Industrial	-0.04***	-0.02	-0.06***
	(-4.80)	(-1.33)	(-4.67)
Multifamily	-0.16***	-0.14***	-0.17***
	(-19.80)	(-10.13)	(-14.03)
Constant	10.20***	11.92***	9.59***
	(137.30)	(42.13)	(25.00)
Observations	26,908	9,260	8,989
State FE	YES	YES	YES
Quarter FE	YES	YES	YES
Adj. R-squared	0.858	0.842	0.878

This table presents the result of an OLS regression of loan interest rate on the over-estimation of NOI and loan characteristics. Loan interest rate is the annualize coupon charged to the borrower. In the case of floating rate loans, the dependent variable is the spread between interest rate and the benchmark interest rate (e.g., Libor). Over-estimation of NOI is calculated by comparing UW NOI and Realized NOI of origination year following Equation 1.3. All regressions include state fixed effects and quarter of origination fixed effects. Standard errors are sandwich estimators. *T*-statistics are presented in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table 6: Effect of Over-estimation by Originator on Delinquency

Delinquency	(1) Model	(2) Model	(3) Model
Average Over-estimation by Originator			20.03***
			(5.87)
LTV	46.26***	32.32***	29.66***
	(15.36)	(9.23)	(9.12)
DSCR	0.97	0.64***	0.63***
	(-0.54)	(-3.13)	(-3.18)
Log Loan Balance	1.10***	1.11***	1.13***
	(4.56)	(4.12)	(4.59)
Coupon	1.53***	1.34***	1.34***
	(13.01)	(9.65)	(9.66)
Term	1.01***	1.00***	1.00***
	(15.12)	(9.74)	(9.65)
Fixed	2.19***	1.46***	1.91***
	(5.93)	(2.69)	(4.40)
Multiple Property	1.50***	1.67***	1.63***
	(3.97)	(4.02)	(3.78)
Partial Amortization	1.49***	1.51***	1.43***
	(4.42)	(3.37)	(2.89)
Full Amortization	1.60***	1.64***	1.58***
	(5.70)	(4.65)	(4.29)
Retail	0.70***	0.65***	0.66***
	(-7.32)	(-6.89)	(-6.64)
Lodging	0.62***	0.60***	0.60***
	(-6.48)	(-5.54)	(-5.47)
Industrial	0.59***	0.51***	0.52***
	(-8.67)	(-8.24)	(-7.93)
Multifamily	0.50***	0.56***	0.55***
	(-9.82)	(-6.76)	(-6.83)
Observations	59,013	28,541	28,541
State FE	YES	YES	YES
Quarter FE	YES	YES	YES
Pseudo R-squared	0.0662	0.0607	0.0634

This table presents the odds ratios of a logistic regression where delinquency status is the dependent variable. Delinquency is an indicator variable that equals one if the loan is delinquent for ninety days or more, in foreclosure, REO, default. Average Over-estimation by Originator is average Over-estimation of NOI aggregated by originators. Over-estimation of NOI is calculated by comparing UW NOI and Realized NOI of origination year following Equation 1.3. Regression in Models (1) and (2) presents the result for base line regression without Average Over-estimation by Originator. Model (1) includes all samples from 1995 to 2006, Model (2) includes a sample where over-estimation data is available, and Model (3) presents the result of regression with Average Over-estimation by Originator. All regressions include state fixed effects and quarter of origination fixed effects. Standard errors are sandwich estimators. T-statistics are presented in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 7: Whether Over-estimation is Priced Sufficiently

	(1)	(2)	(3)
Dependent Variable	Coupon	Delinquency	Delinquency
Over-estimation	0.06***	4.05***	
	(6.06)	(6.42)	
Coupon			2.68***
			(15.21)
LTV	0.36***	20.76***	15.39***
	(13.08)	(18.59)	(21.65)
DSCR	-0.01***	0.44***	0.41***
	(-4.26)	(7.90)	(7.88)
Log Loan Balance	-0.12***	0.23	0.56***
	(-29.62)	(1.43)	(5.74)
Term	0.00***	0.03***	0.02***
	(16.73)	(9.77)	(16.55)
Fixed	-0.29***	1.38	0.82*
	(-9.27)	(1.14)	(1.70)
Multiple Property	0.07***	2.54**	2.44***
	(3.29)	(2.12)	(3.64)
Partial Amortization	0.32***	3.97***	2.04***
	(21.99)	(5.62)	(4.52)
Full Amortization	0.21***	4.03***	2.64***
	(16.23)	(6.10)	(6.23)
Retail	-0.06***	-3.16***	-2.84***
	(-8.53)	(-6.06)	(-8.79)
Lodging	0.07***	-3.44***	-3.74***
	(6.55)	(-4.96)	(-8.64)
Industrial	-0.04***	-3.50***	-3.58***
	(-4.67)	(-6.33)	(-10.59)
Multifamily	-0.15***	-4.14***	-4.08***
	(-17.84)	(-7.99)	(-12.78)
Constant	7.97***	-17.13***	-34.76***
	(141.78)	(-5.99)	(-15.35)
Observations	29,785	29,785	75,906
State FE	YES	YES	YES
Quarter FE	YES	YES	YES
Adj. R-squared	0.857	0.0782	0.0992

This table presents three regression results related to the question of whether over-estimation is priced insufficiently. U.S. non-agency CMBS deals issued between 1995 and 2006 are included. Model (1) has the coupon/spread at origination as dependent variable and it shows the relationship between coupon and over-estimation. Model (2) has delinquency as the dependent variable and shows the relationship between delinquency and over-estimation. Model (3) has delinquency as the dependent variable and shows the relationship between delinquency and the coupon/spread at origination. All dependent variables are in percentages. All regressions include year fixed effects. Standard errors are sandwich estimators. T-statistics are presented in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 8: Regression of AAA Subordination Level on Average Over-estimation by Deal

AAA Subordination Level	(1) Model	(2) Model	(3) Model
Average Over-estimation by Deal		0.91	
		(0.43)	
Average Over-estimation by Deal (2nd)			0.32
			(1.35)
Deal WAC Spread	0.78**	0.26	1.32***
	(2.02)	(0.58)	(3.73)
LTV	0.16**	0.33***	0.13*
	(2.04)	(4.81)	(1.74)
DSCR	-0.49	-0.06	-1.81
	(-0.28)	(-0.05)	(-1.29)
Zero or Negative Amortization	0.10***	0.04	0.05
	(3.10)	(1.13)	(1.55)
Partial Amortization	0.07*	0.06	0.05
	(1.81)	(1.35)	(1.41)
Num of Loans	-0.01*	-0.00	-0.00
	(-1.77)	(-0.30)	(-0.39)
Log Deal Balance	-4.20***	-2.65	-3.07**
	(-3.70)	(-1.63)	(-2.22)
Office	-0.05	-0.01	-0.04
	(-1.51)	(-0.18)	(-1.03)
Retail	-0.09***	-0.04	-0.04
	(-3.48)	(-1.25)	(-1.32)
Hotel	0.07	-0.00	0.05
	(1.43)	(-0.03)	(1.03)
Industrial	-0.09***	0.00	-0.04
	(-2.75)	(0.05)	(-1.34)
Constant	96.20***	48.00*	73.55***
	(4.34)	(1.71)	(2.93)
Observations	349	215	296
Year FE	YES	YES	YES
Adj. R-squared	0.634	0.665	0.675

This table presents the regression result of AAA subordination level on average over-estimation by deal and other deal characteristics. The dependent variable of this regression is AAA subordination level, which is the percentage of the tranche of a deal below a AAA rating. The AAA subordination level measures the safety cushion for the deal against losses. I require at least 40% of the loans to have over-estimation available to be included in the regression. U.S. non-agency CMBS deals issued between 2000 and 2006 are included. All regressions include year fixed effects. Standard errors are sandwich estimators. T-statistics are presented in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 9: Summary Statistics

	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max
	Prior Crisis (2000–2008)					Post Crisis (2009–2014*)				
AAA Subordination Level (%)	16.3	13.9	6.8	2.4	88.0	29.1	23.1	12.1	11.0	63.6
Loan-to-Value Ratio (%)	66.6	68.5	7.1	4.8	89.5	58.9	61.5	8.2	36.9	81.2
Debt-service Coverage Ratio	1.6	1.5	0.3	1.1	3.5	2.3	1.9	1.0	1.4	7.4
Share of Full-Interest-Only Loan (%)	23.1	15.0	25.2	0.0	100.0	37.5	17.0	41.0	0.0	100.0
Share of Partial-Interest-Only Loan (%)	25.2	24.0	19.5	0.0	100.0	18.6	16.8	21.3	0.0	100.0
Number of Loans	148.3	138.0	85.9	1.0	899.0	40.8	45.5	36.4	1.0	208.0
Deal Balance (Millions)	1720.3	1335.5	1136.2	51.0	7903.0	908.4	1001.5	460.0	160.0	2625.0
Deal Spread on 10 Year Treasury Yield (%)	1.6	1.4	1.0	-0.7	10.0	2.2	2.2	1.0	-0.6	6.8
Share of Office Property Loans (%)	30.1	27.7	17.0	0.0	100.0	20.7	14.0	24.7	0.0	100.0
Share of Retail Property Loans (%)	29.4	29.1	15.5	0.0	100.0	36.3	33.8	31.4	0.0	100.0
Share of Hotel Property Loans (%)	9.8	7.2	11.8	0.0	100.0	21.1	11.5	30.0	0.0	100.0
Share of Industrial Property Loans (%)	15.0	10.6	16.4	0.0	100.0	13.8	10.6	18.2	0.0	100.0
Share of Multifamily Property Loans (%)	15.7	13.6	12.0	0.0	92.3	8.0	3.2	14.7	0.0	100.0

The table presents the summary statistics for the AAA subordination level (1-p) and CMBS deal characteristics for samples used in the paper. The detailed definitions of variables are available in the data section. We break down the sample by before financial crisis (2000–2008) and after financial crisis (2009–2014). Partial data is available for 2014 vintage.

Table 10: Main Estimation Results

	Normal Transformation: $\Phi^{-1}(p)$			Logit Transformation: $\log(\frac{p}{1-p})$		
	Model (1)	Model (2)	Model (3)	Model (1')	Model (2')	Model (3')
p_t^e		3.371^{***}	3.646^{***}		5.785^{***}	6.407^{***}
		(0.063)	(0.051)		(0.114)	(0.109)
Delinquency			0.000			0.000
			(0.001)			(0.001)
LTV	-0.598^{***}	-0.049	0.030	-1.028^{***}	-0.085	0.054
	(0.148)	(0.064)	(0.051)	(0.259)	(0.116)	(0.109)
DSCR	-0.076^{***}	0.010	0.034^{**}	-0.126^{***}	0.018	0.078^{***}
	(0.020)	(0.008)	(0.011)	(0.034)	(0.014)	(0.024)
Zero/Neg. Amt.	-0.214^{***}	0.056^{***}	0.027	-0.343^{***}	0.121^{***}	0.056
	(0.037)	(0.015)	(0.015)	(0.064)	(0.027)	(0.032)
Partial Amt.	0.134^{**}	0.026	0.073^{***}	0.249^{**}	0.060	0.159^{***}
	(0.048)	(0.020)	(0.015)	(0.084)	(0.035)	(0.032)
# of Loans (1000)	0.882^{***}	0.164^{**}	0.081^{*}	1.593^{***}	0.366^{**}	0.182^{*}
	(0.131)	(0.063)	(0.039)	(0.230)	(0.113)	(0.083)
Log Deal balance	0.209^{***}	-0.020^{*}	-0.016^{*}	0.352^{***}	-0.041^{**}	-0.034^{*}
	(0.017)	(0.008)	(0.007)	(0.030)	(0.015)	(0.014)
Deal Spread	-2.637^{*}	-0.482	0.107	-5.004^{**}	-1.340	0.148
	(1.028)	(0.421)	(0.364)	(1.798)	(0.763)	(0.776)
Office	0.299^{***}	0.006	0.066^{**}	0.517^{***}	0.005	0.148^{**}
	(0.061)	(0.024)	(0.025)	(0.106)	(0.044)	(0.053)
Retail	0.335^{***}	-0.062^{**}	0.009	0.559^{***}	-0.130^{***}	0.019
	(0.058)	(0.022)	(0.026)	(0.101)	(0.039)	(0.055)
Industrial	0.175^{**}	0.015	0.068^{**}	0.298^{**}	0.010	0.147^{**}
	(0.065)	(0.025)	(0.025)	(0.114)	(0.046)	(0.053)
Multifamily	0.187^{*}	-0.048	0.017	0.313	-0.102	0.046
	(0.092)	(0.038)	(0.032)	(0.160)	(0.069)	(0.068)
(Intercept)	-3.227^{***}	-1.400^{***}	-1.849^{***}	-5.442^{***}	-2.287^{***}	-3.277^{***}
	(0.366)	(0.154)	(0.141)	(0.640)	(0.279)	(0.301)
Adj. R^2	0.608	0.939	0.960	0.599	0.932	0.942
Num. obs.	632	632	453	632	632	453

The table presents the estimation results. The dependent variable is $\Phi^{-1}(p)$. Model (1) does not include peer effects. In Model (2), we include peer effects as a regressor; see (2.7). In Model (3), we include the delinquency at third year as one of the explanatory variables. Note that Model (1) is nested in our specification. Models (1'), (2') and (3') are similar to Models (1), (2) and (3), respectively, except that our dependent variable uses the logit transformation, that is, $\text{logit}(p) = \log(\frac{p}{1-p})$. Moreover, ***p<0.01, **p<0.05, *p<0.1.

Table 11: Numerical Rating Value Assignment

Standard & Poor's	Moody's	Fitch	DBRS	KBRA	Numerical Rating Value
AAA	Aaa	AAA	AAA	AAA	23
AA+	Aa1	AA+	AAH	AA+	22
AA	Aa2	AA	AA	AA	21
AA-	Aa3	AA-	AAL	AA-	20
A+	A1	A+	AH	A+	19
A	A2	A	A	A	18
A-	A3	A-	AL	A-	17
BBB+	Baa1	BBB+	BBBH	BBB+	16
BBB	Baa2	BBB	BBB	BBB	15
BBB-	Baa3	BBB-	BBBL	BBB-	14
BB+	Ba1	BB+	BBH	BB+	13
BB	Ba2	BB	BB	BB	12
BB-	Ba3	BB-	BBL	BB-	11
B+	B1	B+	BH	B+	10
B	B2	B	B	B	9
B-	B3	B-	BL	B-	8
CCC+	Caa1	CCC	CCCH	CCC+	7
CCC	Caa2	CCC	CCC	CCC	6
CCC-	Caa3	CCC	CCCL	CCC-	5
CC	Ca	CCC	CCH	CC	4
C	Ca	CCC	CH	C	3
D	C	DDD	D	D	2
NR	WR	WD	NR	NR	1

This table presents the mapping between alphabetical ratings to assigned numerical rating values for S&P's, Moody's, Fitch, DBRS, and KBRA, respectively. The alphabetical rating scales are directly comparable among the five rating agencies. Value 2 corresponds to "default" and value 1 corresponds to "not rated."

Table 12: Summary Statistics: Deal and Tranche Level Information

Variable	N	Mean	Std. Dev.	Min	Max
Panel A. Deal Level Information					
AAA Subordination Level	177	29.61	12.13	15.75	63.57
LTV	177	58.93	8.37	36.90	81.22
DSCR	177	2.28	1.01	1.37	7.40
Zero/Negative Amortization	177	38.38	41.02	0.00	100.00
Partial Amortization	177	19.49	21.57	0.00	100.00
Num of Loans	177	41.08	35.54	1.00	208.00
Deal Balance (Millions)	177	142.00	171.00	22.50	1180.00
Deal Spread	177	2.22	0.96	-0.64	6.83
Office	177	21.20	25.20	0.00	100.00
Retail	177	35.37	31.06	0.00	100.00
Hotel	177	22.30	30.51	0.00	100.00
Industrial	177	13.28	17.32	0.00	100.00
Multifamily	177	7.86	13.38	0.00	100.00
Panel B. Tranche Level Information					
Number of Ratings	5092	2.45	0.64	1	4
Rated by SAP	5092	0.30	0.46	0	1
Rated by MDY	5092	0.78	0.42	0	1
Rated by Fitch	5092	0.64	0.48	0	1
Rated by DBRS	5092	0.31	0.46	0	1
Rated by KBRA	5092	0.54	0.50	0	1
Numeric Rating SAP	1495	19.09	4.29	8	23
Numeric Rating MDY	3649	19.80	4.33	8	23
Numeric Rating Fitch	3121	19.44	4.53	8	23
Numeric Rating DBRA	1554	19.86	4.45	8	23
Numeric Rating KBRA	2647	19.87	4.32	8	23

This table presents the summary statistics for deal level and tranche level data. CMBS issued between January 2011 and May 2014 with available information are covered.

Table 13: Summary Statistics: Loan Level Information

Variable	N	Mean	Std. Dev.	Min	Max
Panel A. Calibration Period (2005-2008)					
Delinquency	35753	0.14	0.35	0	1
LTV	35540	0.68	0.13	0.01	1.21
DSCR	35616	1.50	1.19	-0.13	79.41
Log Loan Balance	35747	15.57	1.30	-4.61	22.29
Term	35753	144.07	81.21	9	480
Fixed	35753	0.89	0.31	0	1
Multiple Property	35753	0.05	0.22	0	1
Zero/Negative Amortization	35753	0.18	0.38	0	1
Partial Amortization	35753	0.13	0.33	0	1
Full Amortization	35753	0.69	0.46	0	1
Office	35753	0.17	0.37	0	1
Retail	35753	0.31	0.46	0	1
Hotel	35753	0.10	0.30	0	1
Industrial	35753	0.16	0.37	0	1
Multifamily	35753	0.26	0.44	0	1
Panel B. Testing Period (2011-2014)					
Delinquency	4518	0.00	0.05	0	1
LTV	4514	0.65	0.10	0.01	0.87
DSCR	4047	1.84	1.57	0.66	88.02
Log Loan Balance	4518	16.42	1.14	13.26	21.65
Term	4518	110.48	39.93	14	360
Fixed	4518	0.97	0.17	0	1
Multiple Property	4518	0.11	0.31	0	1
Zero/Negative Amortization	4518	0.11	0.31	0	1
Partial Amortization	4518	0.20	0.40	0	1
Full Amortization	4518	0.70	0.46	0	1
Office	4518	0.13	0.34	0	1
Retail	4518	0.26	0.44	0	1
Hotel	4518	0.18	0.38	0	1
Industrial	4518	0.15	0.36	0	1
Multifamily	4518	0.28	0.45	0	1

This table presents the summary statistics for loan level data. I break down the sample by calibration period (2005-2008) and testing period (2011-2014). Partial data is available for 2014 vintage.

Table 14: Rating Comparison between the Entrant and the Incumbents

Panel A. Comparison between KBRA and Other Rating Agencies

	KBRA				All except KBRA			
Vintage	N	Mean	95% CI		N	Mean	95% CI	
2011	93	21.5%	13.2%	29.9%	1309	5.0%	3.8%	6.1%
2012	663	12.2%	9.7%	14.7%	2619	5.3%	4.4%	6.2%
2013	1397	13.9%	12.1%	15.7%	4407	8.9%	8.1%	9.7%
2014	494	14.0%	10.9%	17.0%	1484	8.2%	6.8%	9.6%
Total	2647	13.8%	12.4%	15.1%	9819	7.3%	6.8%	7.8%

Panel B. Example

Deal Ticker	Class	KBRA	SAP	MDY	FITCH	DBRS
GSMS 2012-TMSQ	A	23	23			
GSMS 2012-TMSQ	B	22	20			
GSMS 2012-TMSQ	C	18	17			
GSMS 2012-TMSQ	D	16	15			
GSMS 2012-TMSQ	XA	23	23			
GSMS 2012-TMSQ	XB	23	20			

This table presents the percentage of “over-rate” (i.e. the situation where the rating agency issues a higher rating than the one issued by any of the other agencies). Panel A shows the results by comparing KBRA with the remaining rating agencies over years 2011-2014. Panel B presents an example in which KBRA “over-rate” the CMBS deal where Class B, C, D, and XB obtained higher ratings from KBRA than SAP. Partial data is available for 2014 vintage.

Table 15: Relationship between the CMBS rated by KBRA and AAA Subordination Level

AAA Subordination Level	(1) Model	(2) Model
Rated by KBRA		-2.25**
		(-2.21)
LTV	0.18	0.18
	(1.31)	(1.35)
DSCR	-0.13	-0.15
	(-0.10)	(-0.12)
Zero/Negative Amortization	0.08***	0.08***
	(3.47)	(3.64)
Partial Amortization	-0.04	-0.04
	(-1.31)	(-1.24)
Num of Loans	-0.13***	-0.13***
	(-3.42)	(-3.50)
Log Deal Balance	-5.04***	-5.04***
	(-3.26)	(-3.32)
Deal Spread	0.24	0.15
	(0.30)	(0.19)
Office	-0.02	-0.01
	(-0.28)	(-0.23)
Retail	-0.07	-0.06
	(-1.37)	(-1.19)
Hotel	0.07	0.07
	(1.16)	(1.20)
Multifamily	0.07	0.07
	(1.18)	(1.16)
Constant	122.79***	122.34***
	(3.94)	(4.04)
Observations	177	177
Year FE	YES	YES
Adj. R-squared	0.749	0.756

This table presents the regression results, which show how the average rating for CMBS deals rated by KBRA compares to deals rated by other agencies. The dependent variable of this regression is AAA subordination level, which is the proportion of the deal below a AAA rating. The $RatedbyKBRA$ is an indicator variable that equals one if the deal is rated by KBRA. Model (1) shows the benchmark regression with the indicator variable and Model (2) shows the full regression. U.S. non-agency CMBS deals issued between 2011-2014 are included. Partial data is available for 2014 vintage.

Table 16: Relationship between Delinquency and Loan Characteristics

Delinquency	(1) Model	(2) Model	(3) Model	(4) Model
LTV	0.39***	84.17***	0.22***	15.93***
	(29.85)	(19.37)	(28.07)	(13.09)
DSCR	0.01***	0.50***	0.00***	0.27***
	(7.30)	(-7.53)	(6.57)	(-15.64)
Log Loan Balance	-0.00**	0.97**	-0.00***	1.00
	(-2.07)	(-2.11)	(-2.88)	(-0.20)
Term	0.00***	1.00***	0.00***	1.00***
	(3.53)	(4.85)	(13.03)	(12.90)
Fixed	0.01	1.17**	0.01*	0.99
	(1.28)	(2.56)	(1.79)	(-0.26)
Multiple Property	0.04***	1.42***	0.04***	1.55***
	(4.43)	(4.44)	(7.02)	(6.49)
Partial Amortization	0.03***	1.33***	-0.02***	0.64***
	(4.98)	(3.93)	(-5.40)	(-7.15)
Full Amortization	0.06***	1.64***	0.02***	1.12**
	(12.61)	(9.24)	(6.62)	(2.25)
Retail	-0.05***	0.71***	-0.04***	0.70***
	(-7.82)	(-7.60)	(-9.66)	(-9.26)
Hotel	-0.04***	0.87**	-0.01***	1.01
	(-5.47)	(-2.11)	(-2.91)	(0.18)
Industrial	-0.06***	0.62***	-0.04***	0.65***
	(-9.44)	(-8.52)	(-9.82)	(-8.78)
Multifamily	-0.06***	0.58***	-0.06***	0.49***
	(-10.26)	(-10.70)	(-14.77)	(-16.39)
Constant	-0.15***	0.01***	0.85***	0.06***
	(-3.67)	(-5.58)	(44.23)	(-3.45)
Observations	37,028	37,023	66,511	66,504
State FE	YES	YES	YES	YES
Adj. R-squared	0.0633		0.0449	
Pseudo R-squared		0.0918		0.0911

This table presents the regression results for calibration of prediction model on CMBS loan level delinquency prediction. Delinquency is an indicator variable that equals one if the loan is delinquent for ninety days or more, is in foreclosure, REO, default. Models (1) and (3) follow an OLS regression and Models (2) and (4) follow logistic regression. Models (1) and (2) include samples from 2005-2008 and Models (3) and (4) include samples from 2000-2008. All regressions include state fixed effects. Partial data is available for 2014 vintage.

Table 17: Relationship between Predicted Delinquency Probability and Being Rated by KBRA

Predicted Probability of Delinquency	(1) Model	(2) Model	(3) Model	(4) Model
Rated by KBRA	0.013***	0.007***	0.016***	0.005***
	(5.661)	(3.342)	(6.164)	(3.710)
Constant	0.123***	0.102***	0.091***	0.069***
	(19.411)	(19.168)	(12.863)	(19.156)
Observations	5,735	5,733	5,735	5,733
R-squared	0.048	0.055	0.159	0.071
Quarter FE	YES	YES	YES	YES
Adj. R-squared	0.0452	0.0529	0.157	0.0685

This table presents the regression results with predicted probability of delinquency as the dependent variable. The explanatory $RatedbyKBRA$ is an indicator variable that equals one if the deal is rated by KBRA. The Models in this regression correspond to the four predictions Models presented in the last table. All regressions includes quarter fixed effects. Partial data is available for 2014 vintage.

Appendix

Appendix 1

Proofs in Chapter 2

1.1 Proofs of Lemma 1

Proof. The non–identification result under a single equilibrium is straightforward given the discussions in this subsection. It suffices to show identification under multiple equilibria. By (2.6), we have

$$\mathbb{E}[\Phi^{-1}(p)|x,t] = \beta(x) + \alpha\mathbb{E}(p|x,t) + \mathbb{E}(\epsilon|x,t), \quad t = 0, 1.$$

Note that $t = 0, 1$ represent the selection of different equilibria before and after crisis. Therefore, the distribution of ϵ given x is invariant for $t = 0, 1$. Hence, $\mathbb{E}(\epsilon|x,t) = \mathbb{E}(\epsilon|x) = 0$. Hence,

$$\mathbb{E}[\Phi^{-1}(p)|x,t] = \beta(x) + \alpha\mathbb{E}(p|x,t), \quad t = 0, 1.$$

It follows that

$$\mathbb{E}[\Phi^{-1}(p)|x,t=1] - \mathbb{E}[\Phi^{-1}(p)|x,t=0] = \alpha\Big[\mathbb{E}(p|x,t=1) - \mathbb{E}(p|x,t=0)\Big]$$

from which we can identify α as

$$\alpha = \frac{\mathbb{E}[\Phi^{-1}(p)|x,t=1] - \mathbb{E}[\Phi^{-1}(p)|x,t=0]}{\mathbb{E}(p|x,t=1) - \mathbb{E}(p|x,t=0)}.$$

Moreover,

$$\beta(x) = \mathbb{E}[\Phi^{-1}(p)|x,t=1] - \alpha\mathbb{E}(p|x,t=1).$$

Hence, $(\alpha, \beta(\cdot))$ can be uniquely derived from the joint distribution of $F_{p|x,t}$.

$\square$

1.2 Proofs of Theorem 1

Proof. We first show consistency, that is, $\hat{\theta} \xrightarrow{p} \theta_0$. Note that

$$\hat{\theta}-\theta_0 = \hat{A}^{-1} \times \frac{1}{n}\sum_{i=1}^{n} \hat{\sigma}_i^2 \hat{w}_i (w_i' - \hat{w}_i')\theta_0 + \hat{A}^{-1} \times \frac{1}{n}\sum_{i=1}^{n} \hat{\sigma}_i^2 \hat{w}_i \epsilon_i = \alpha_0 \times \hat{A}^{-1}\hat{B} + \hat{A}^{-1}\hat{C},$$

where $\hat{B} \equiv \frac{1}{n}\sum_{i=1}^{n}(\hat{\psi}_i, \hat{\sigma}_i x_i')'(\hat{\psi}_i - \psi_i)$, $\hat{C} \equiv \frac{1}{n}\sum_{i=1}^{n} \hat{\sigma}_i^2 \hat{w}_i \epsilon_i = \frac{1}{n}\sum_{i=1}^{n}(\hat{\sigma}_i \hat{\psi}_i \epsilon_i, \hat{\sigma}_i^2 \epsilon_i x_i')'$ and

$$\hat{A} \equiv \frac{1}{n}\sum_{i=1}^{n} \hat{\sigma}_i^2 \hat{w}_i \hat{w}_i' = \frac{1}{n}\sum_{i=1}^{n} \begin{pmatrix} \hat{\psi}_i^2 & \hat{\psi}_i \hat{\sigma}_i x_i' \\ \hat{\sigma}_i x_i \hat{\psi}_i & \hat{\sigma}_i^2 x_i x_i' \end{pmatrix}.$$

By definition, $\hat{A}$, $\hat{B}$ and $\hat{C}$ are V-statistics. By the law of large number of V-statistics,

$$\hat{A} \xrightarrow{p} A \equiv \begin{pmatrix} \mathbb{E}\left\{\left[p^e(x,t) f_{x|t}(x|t)\right]^2\right\} & \mathbb{E}\left\{p^e(x,t) f_{x|t}^2(x|t) x'\right\} \\ \mathbb{E}\left\{p^e(x,t) f_{x|t}^2(x|t) x\right\} & \mathbb{E}\left\{\left[f_{x|t}(x|t)\right]^2 x x'\right\} \end{pmatrix}.$$

and $\hat{B} \xrightarrow{p} 0$ and $\hat{C} \xrightarrow{p} 0$. Therefore, $\hat{\theta} \xrightarrow{p} \theta_0$.

Next, we derive the asymtotic distribution of $\hat{\theta}$. Let $\tilde{B} \equiv \frac{1}{n}\sum_{i=1}^{n}(\psi_i, \sigma_i x_i')'(\hat{\psi}_i - \psi_i)$, $\tilde{C} \equiv \frac{1}{n}\sum_{i=1}^{n}(\sigma_i \psi_i \epsilon_i, \sigma_i^2 \epsilon_i x_i')'$. Following **?**, given $nh^{2d} \to \infty$, we have

$$\sqrt{n}(\hat{B} - \tilde{B}) = o_p(1), \quad \sqrt{n}(\hat{C} - \tilde{C}) = o_p(1).$$

Moreover, let $\delta_0 = \mathbb{E}[(p^e(x,t), x')' p^e(x,t) f_{x|t}^2(x|t)]$. Following **?**, there is

$$\sqrt{n}\Big(\frac{1}{n}\sum_{i=1}^{n}(\psi_i, \sigma_i x_i')'\hat{\psi}_i - \delta_0\Big) = \frac{2}{\sqrt{n}}\sum_{i=1}^{n}\Big((\psi_i, \sigma_i x_i')'\psi_i - \delta_0\Big) + o_p(1).$$

It follows that

$$\sqrt{n}(\tilde{B}-\delta_0) = \frac{1}{\sqrt{n}}\sum_{i=1}^{n}\Big((\psi_i, \sigma_i x_i')'\psi_i - \delta_0\Big) + o_p(1).$$

Therefore, applying the central limit theorem, we have

$$\sqrt{n}\left(\begin{array}{c} \tilde{B}-\delta_0 \\ \tilde{C}-0 \end{array}\right) \xrightarrow{d} N\left(0, \left(\begin{array}{cc} \Sigma_B & \Sigma_{BC} \\ \Sigma_{CB}' & \Sigma_C \end{array}\right)\right)$$

where

$$\Sigma_B = \left(\begin{array}{cc} \mathrm{Var}(\psi^2) & \mathrm{Cov}(\psi^2, f_{x|t}(x|t)\psi x') \\ \mathrm{Cov}(\psi^2, f_{x|t}(x|t)\psi x) & \mathrm{Var}(f_{x|t}(x|t)\psi x) \end{array}\right),$$
$$\Sigma_C = \sigma_\epsilon^2 \left(\begin{array}{cc} \mathbb{E}(f_{x|t}^2(x|t)\psi^2) & \mathbb{E}(f_{x|t}^3(x|t)\psi x') \\ \mathbb{E}(f_{x|t}^3(x|t)\psi x) & \mathbb{E}(f_{x|t}^4(x|t)xx') \end{array}\right),$$

and $\Sigma_{BC} = \Sigma_{CB}' = 0$. Therefore,

$$\sqrt{n}(\hat{\theta}-\theta_0) \xrightarrow{d} N(0, A^{-1}(\alpha_0^2\Sigma_B + \Sigma_C)A^{-1}). \quad \square$$

Bibliography